Finance and Economics Discussion Series

Federal Reserve Board, Washington, D.C.
ISSN 1936-2854 (Print)
ISSN 2767-3898 (Online)

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2024-066

Please cite this paper as:
Brunetti, Celso, Matthew Carl, Jacob Gerszten, Chiara Scotti, and Chaehee Shin (2024). "Interconnectedness in the Corporate Bond Market," Finance and Economics Discussion Series 2024-066. Washington: Board of Governors of the Federal Reserve System, https://doi.org/10.17016/FEDS.2024.066.

Interconnectedness in the Corporate Bond Market

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April 2024

ABSTRACT

Does interconnectedness improve market quality? Yes.
We develop an alternative network structure, the assets network: assets are connected if they are held by the same investors. We use several large datasets to build the assets network for the corporate bond market. Through careful identification strategies based on the COVID-19 shock and "fallen angels," we find that interconnectedness improves market quality especially during stress periods. Our findings contribute to the debate on the role of interconnectedness in financial markets and show that highly interconnected corporate bonds allow for risk sharing and require a lower compensation for risk.

Keywords: financial stability, interconnectedness, institutional investors, big data

JEL Classification Codes: C13, C55, C58, G1

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1. Introduction

The notion of "interconnectedness" became popular with the Great Financial Crisis (GFC). Linkages between markets and institutions as well as the ramifications of financial distress to the real economy put interconnectedness in the limelight. In fact, interconnectedness is now part of the regulatory framework.[1] Interconnectedness is a sophisticated concept: too little interconnectedness (sparse network) may impede market functioning, and too much interconnectedness (dense network) may exacerbate the effects of a shock. The goal of this paper is to study the linkages between interconnectedness and market quality.

We choose the corporate bond market as our sandbox. This market has grown substantially in recent years and represents an important source of funding for the corporate sector.[2] It is dominated by institutional investors, which allows us to map linkages among the largest market players such as insurance companies and mutual funds. Compared to equity markets, its liquidity and market functioning in the corporate bond market have been under much scrutiny, leading to a rapid development of the literature (see, Boyarchenko et al., 2021; Dick-Nielsen and Rossi, 2019; Trebbi and Xiao, 2019). Finally, the corporate bond market experienced significant disruptions in March 2020 because of the COVID-19 pandemic (see, Haddad and Muir, 2021). Hence, studying how interconnectedness relates to market quality in both tranquil times as well as in times of distress is particularly informative.

In this paper, we develop an alternative and complementary network structure—the assets network—which mirrors the traditional notion of a portfolio similarity network. This new network construct is derived at the asset level and is based on the idea that assets are interconnected if they are held by the same investors.

The more traditional portfolio similarity network captures spillover effects due to overlapping portfolios: two financial institutions with similar portfolios are linked because a shock to one financial institution has repercussions on the other financial institution through

[1] Interconnectedness is one of the criteria used by the Financial Stability Board to designate Global Systemically Important Banks (G-SIBs). In the U.S., interconnectedness is also used by the Financial Stability Oversight Council (FSOC) to designate nonbank Systemically Important Financial Institutions (SIFIs).

[2] It has reached over $15 trillion as of Q4 2023–see Financial Account of the U.S.

their common asset holdings (see, Caccioli et al., 2015). In contrast, our network construct captures linkages among assets given that these assets are held by several financial institutions. The emphasis of our network is on the assets as opposed to financial institutions. Studying the network of assets is fundamentally important for several reasons. First, it allows us to investigate how interconnectedness of financial assets is linked to asset-specific characteristics such as liquidity and volatility and, more generally, to market quality. Second, there is a growing literature on institutional asset pricing; our network structure provides another lens through which to study how assets held by several institutions—our assets network—impact the pricing process. This is particularly relevant in our framework which analyzes corporate bond holdings by large investors. Third, assets interconnectedness provides an alternative and unique perspective on how financial assets are linked in contrast to correlation analysis. Diebold and Yılmaz (2014) and Billio et al. (2012) construct assets networks based on the variance-covariance matrix of returns. Our network builds edges based on whether assets are held by common investors, and is, therefore, potentially more accurate because it does not require estimating any moment of the returns distribution (see, Adamic et al., 2017). Finally, the traditional overlapping portfolio network puts emphasis on financial institutions and is more suited for an entity-based supervisory approach, while our assets network may provide useful for an activity-based approach for regulation.[3]

We first focus on the interconnectedness of the corporate bond market, leveraging the rich information available in the Thomson Reuters eMAXX database, which contains data on corporate bond holdings at the institutional investor-bond-year-quarter level. We build a network of corporate bonds and measure their interconnectedness using cosine similarity. As expected, we find that bonds issued by large firms are part of the portfolio of many investors and form the core of our networks, while smaller bond issuers comprise the periphery—implying that only a few investors hold these bonds. We also match the interconnectedness measures of corporate bonds with the TRACE database that has security-level data on corporate bond trading volume, liquidity, and volatility.

The new interconnectedness construct and the complexity of our data allow us to use a rich panel regression analysis to investigate the link between interconnectedness and spread,

[3] See, Borio et al. (2022).

liquidity, and volatility of corporate bonds. We find that the higher the interconnectedness of an asset—meaning that the asset is common to many investors' portfolios—the lower its spread and the higher its liquidity. This result highlights that, as expected, corporate bonds that are held across several portfolios require a lower compensation for risk and are more liquid. This relation is, however, affected by market conditions. We explore the heterogeneous effects of interconnectedness throughout the conditional distribution of the response variables (spreads, liquidity, and volatility), while controlling for bond characteristics, through a panel data quantile regression. We find that the relation we have just highlighted is stronger when a financial asset is under stress, i.e. the spread and liquidity of an asset are in the upper tail of their conditional distributions. Altogether, higher interconnectedness is associated with lower spreads and volatility, and higher liquidity in normal market conditions (mean effect) and these results are stronger when markets are distressed (as shown by quantile regressions).[4]

While the analysis thus far documents linkages between interconnectedness and market quality measures, we are interested in determining causality. That is, we are interested in understanding whether higher interconnectedness reduces spreads, increases liquidity, and tames volatility. This is a fundamental issue. On the one hand, Allen and Gale (2000) develops a model in which complete networks (high interconnectedness) help mitigate the effects of a shock through risk sharing and, therefore, are beneficial to financial stability. On the other, Acemoglu et al. (2015) shows that if the shock is too large, high interconnectedness propagates the shock leading to a more fragile financial system. The COVID-19 outbreak represents a large exogenous shock. Following Hassan et al. (2023), we separate bonds issued by firms affected by the shock from bonds issued by firms not affected by the pandemic. We find that the effects of the shock are mitigated when bonds issued by firms exposed to the pandemic are highly interconnected to bonds issued by firms *not* exposed to the shock—spread decreases and liquidity increases. Our results indicate that interconnectedness enables risk sharing and, on net, is beneficial to the corporate bond market.

[4]Our results are robust to different model specifications and to several controls that are known to affect corporate bond pricing dynamics, such as investor concentration and the number of unique investors.

To corroborate these results we also look at "fallen angels:" bonds downgraded from investment grade to high yield. We select bonds with similar characteristics and a credit rating of BBB- (the lowest credit rating in the investment grade category). Only some of these bonds are downgraded in the next period. Since the bonds we consider in this exercise have similar characteristics, the bifurcation between fallen angels and non-fallen angels is plausibly exogenous within the short time window we are considering—the analysis only considers two periods, before and after the downgrade.[5] Our results show that a one standard deviation increase in interconnectedness of a fallen angel substantially decreases spreads and increases liquidity.

Overall, our findings establish that higher levels of interconnectedness are positively linked to market quality. Moreover, the link between interconnectedness and market quality changes over time when market conditions also change. Importantly, this link is stronger during periods of market distress. Finally, interconnectedness is particularly important when large negative shocks hit financial markets (COVID-19) and when major corporate events occur (fallen angels). In these crisis situations, interconnectedness, through risk sharing, promotes market functioning.

Our paper contributes to several strands of the literature. First, we contribute to the interconnectedness literature. Networks in finance have been mapped using three main techniques: (i) correlation networks, in which edges between financial institutions are based on estimates of the variance-covariance matrix of publicly available data, such as asset returns (see, Billio et al., 2012; Diebold and Yılmaz, 2014); (ii) physical networks, in which edges capture contractual agreements among counterparties, such as interbank transactions (see, Brunetti et al., 2019); and (iii) common holdings networks, in which investors are connected if they hold similar portfolios (see, Caccioli et al., 2015; Greenwood et al., 2015; Cetorelli et al., 2023). In this paper, we propose a new approach of mapping financial networks which mirrors the notion of overlapping portfolios, and which we call the *assets network* or *investor similarity network*. Similar to our approach, Antón and Polk (2014) connect stocks commonly held by mutual funds. Their goal is to study how common ownership affects the

[5] Känzig (2021) proposes an identification strategy based on precisely selecting the time frame of specific events, which for us is the downgrade.

cross-sectional correlation in the rate of returns. Our focus is instead on the network structure and its properties. We are interested in fully understanding the interconnectedness of the new network and how it evolves both over time and in different market conditions. In fact, our goal is to provide a new and alternative mapping for financial networks.

Second, we connect to the emerging literature on institutional demand-based asset pricing. One strand of this literature studies the role of intermediaries in asset pricing, such as in Haddad and Muir (2021) and He et al. (2017). Another strand of the literature examines the role of institutional *holders* in asset pricing and, in particular, the composition of institutional investors as a potential state variable in the corporate bond market. For instance, Ben-David et al. (2021) show how the rising concentration of holdings by institutional investors affects stock volatility and price inefficiency, Li and Yu (2022) find that investor concentration is related to bond liquidity, and Li and Yu (2021) and Bretscher et al. (2022) analyze how the composition of institutional investors relates to corporate bond market qualities. Corell et al. (2023) also look at European corporate bonds to find how convenience yields could vary by differing demands from various institutional investors. Overall, this literature tracks back to the demand-based asset pricing approach of Koijen and Yogo (2019). We contribute to this emerging area by showing that the interconnectedness of an asset plays an important role in corporate bond markets.

Finally, we relate to the recent financial stability literature that tries to determine whether high interconnectedness is a vulnerability or a virtue of the financial system. Conflicting views exist in the literature, from Allen and Gale (2000), who find interconnectedness to be a virtue, to more recent empirical works finding evidence for financial linkages and overlapping holdings of assets to be a contagion or fire sales mechanism (Allen et al., 2012; Duarte and Eisenbach, 2021; Falato et al., 2021; Greenwood et al., 2015, among others). Somewhere in between these two conflicting views, many recent works study the non-monotonic tradeoff between contagion and risk sharing, social optimality of interconnectedness, and conditions for which one type of network is better than another (Acemoglu et al., 2015; Cabrales et al., 2017; Elliott et al., 2014, 2021; Gofman, 2017, among others). Our results provide evidence of a causal effect: interconnectedness improves market quality.

The paper is organized as follows. Section 2 describes our novel network approach, illustrating the building blocks of the asset-based network of investor similarity. Section 3 summarizes the wealth of data that we use in the empirical investigation. Section 4 describes the resulting measures that we use in the analysis. Section 5 explains the regression framework and its results, including those for the quantile regressions. Section 6 examines the causal linkages between interconnectedness and market market quality. Section 7 concludes.

2. Network Approach

There are several ways to construct networks in finance. The three main approaches can be briefly described as: (i) correlation networks, which are based on estimates of the variance-covariance matrix of publicly available data such as asset returns (see, Billio et al., 2012; Diebold and Yılmaz, 2014);[6] (ii) physical networks, which reflect contractual agreements between counterparties and capture important aspects of risk such as conterparty risk (see, Brunetti et al., 2019); and (iii) overlapping portfolios networks, which connect investors through their common holdings (see, Caccioli et al., 2015; Greenwood et al., 2015). In this paper, we propose a new approach of mapping financial networks which parallels the notion of overlapping portfolios, but that draws edges between assets rather than institutions.

The starting point is a bipartite network with two sets of nodes: financial institutions or investors (Is) and financial assets (As). As shown in Figure 1a, if a financial institution holds an asset in its portfolio, there is an edge between that asset and that financial institution. For example, because investor I_1 holds asset A_1, there is an edge between I_1 and A_1. The traditional network of overlapping portfolios, or common asset holdings, implies that since A_1 is held also by I_2 and I_3, all three investors are interconnected through their common holdings of A_1. Similarly, because A_2 is held by I_2 and I_3, there is a link between these two investors (see Barucca et al., 2021).

We derive an alternative novel network structure at the asset level, based on the idea that two assets, A_1 and A_2, are interconnected if they are held by the same investor. In Figure 1b,

[6] A related approach adopts quantile regression analyses, see Ando et al. (2021) and Härdle et al. (2016).

A_1 and A_3 are interconnected because both assets are held in the portfolio of investor I_3. Similarly, A_1 and A_2 are also interconnected since they are held by investors I_2 and I_3. In fact, A_1 and A_2 are interconnected to a higher extent than A_1 and A_3 because these assets share two overlapping investors.

This asset-based network allows us to examine important effects of interconnectedness across financial assets. In Figure 1b, interconnectedness between A_1 and A_3 captures and quantifies the following mechanism. Suppose a shock hits A_1 (e.g., downgrade to junk) and reduces its market value. This shock will then negatively impact the performance of the portfolios of all investors, I_1, I_2, and I_3 since they all hold A_1. Investors will be forced to re-balance their portfolios to raise more capital or liquidity (e.g., in the case of mutual funds, to meet redemptions) and the re-balancing will trigger a change in holdings of both A_2 and A_3 because the re-balancing investors also hold A_2 (I_2 and I_3) and A_3 (I_1).

In Figure 1b, our measure of interconnectedness between A_1 and A_2 is stronger than that between A_1 and A_3 because two investors (I_2 and I_3) hold these assets as opposed to just one investor for A_1 and A_3. This network feature implies that the same initial shock on A_1 (and/or I_2 and/or I_3) will likely spill over to A_2 to a greater extent than it will to A_3, since both I_2 and I_3 will re-balance their portfolios as opposed to just one investor (I_3) re-balancing in the case of A_1 and A_3.

Notice that the notion of overlapping investors for a bond is, however, different than the sheer number of investors holding the bond. In Figure 1b, A_1 is held by the highest number of investors (I_1, I_2, and I_3), followed by A_2, which is held by two investors (I_2 and I_3). However, A_1 has the same number of overlapping investors—and degree of interconnectedness—as A_2. This arises because out of the three investors holding A_1, one investor (I_1) does not invest in any other assets, thereby eliminating its propensity to "overlap" with other investors. In general, as we have illustrated in this example, it is possible that assets with fewer investors are more interconnected (have more overlapping investors) than other assets with more investors.

In what follows, we describe our notion of the asset-based network in more detail and highlight the network measure used in the analysis.

2.1. Network of Financial Assets and Institutions

We start by denoting the network of financial assets and financial institutions as $Q = (A, I, \mathbf{E})$, where $A = A_1, A_2, ..., A_S$ is the set of nodes corresponding to financial assets (corporate bonds only, in our case), $I = I_1, I_2, ..., I_N$ represents the set of financial institutions, and $\mathbf{E}$ is a $S \times N$ matrix representing the amount, $E_{i,k}$, held by I_k in A_i:

$$\mathbf{E} = \begin{array}{c|cccc|c} & I_1 & I_2 & \cdots & I_N & \\ \hline A_1 & E_{11} & E_{12} & \cdots & E_{1N} & V_1^A \\ A_2 & E_{21} & E_{22} & \cdots & E_{2N} & V_2^A \\ \vdots & \vdots & \vdots & \ddots & \vdots & \vdots \\ A_S & E_{S1} & E_{S2} & \cdots & E_{SN} & V_S^A \\ \hline & V_1^I & V_2^I & \cdots & V_N^I & \end{array}. \quad (1)$$

Summing across columns gives the total amount of security i held by the system (investors in our data), V_i^A, known as the *strength of the network*:

$$V_i^A = \sum_{k=1}^{N} E_{i,k}, \quad (2)$$

and summing across rows produces the total amount invested by investor k in all assets, V_k^I. Depending on the scope of the analysis, $E_{i,k}$ could be normalized by the total issued amount of asset i outstanding or by V_i^A.

We define as $\mathring{\mathbf{E}}$ the corresponding adjacency matrix

$$
\overset{\circ}{\mathbf{E}} = \begin{array}{c|cccc|c}
 & I_1 & I_2 & \cdots & I_N & \\
\hline
A_1 & \overset{\circ}{E}_{11} & \overset{\circ}{E}_{12} & \cdots & \overset{\circ}{E}_{1N} & D_1^A \\
A_2 & \overset{\circ}{E}_{21} & \overset{\circ}{E}_{22} & \cdots & \overset{\circ}{E}_{2N} & D_2^A \\
\vdots & \vdots & \vdots & \ddots & \vdots & \vdots \\
A_S & \overset{\circ}{E}_{S1} & \overset{\circ}{E}_{S2} & \cdots & \overset{\circ}{E}_{SN} & D_S^A \\
\hline
 & D_1^I & D_2^I & \cdots & D_N^I &
\end{array}, \tag{3}
$$

where the generic element $\overset{\circ}{E}_{i,k} = 1$ if $E_{i,k} > q$ and zero otherwise. The parameter q denotes a threshold and in traditional network analysis $q = 0$.[7]

Similar to before, the sum across columns gives the total number of financial institutions holding security i, D_i^A, known as *network degree*,

$$
D_i^A = \sum_{k=1}^{N} \overset{\circ}{E}_{i,k}, \tag{4}
$$

and the sum across rows generates the total number of assets investor k has invested in, D_k^I.

2.2. Asset-based Network of Investor Similarity

The network we focus on in this paper is derived from the network of financial assets and financial institutions Q described in the previous section and captures interconnectedness among assets based on whether the assets belong to the same portfolios.

We define the network of financial assets as $O^A = \left(A, \mathbf{P}^A\right)$, where $A = \{A_1, A_2, ..., A_S\}$ represents the set of assets, and $\mathbf{P}^A$ is the matrix measuring similarities of assets in terms of investors. Several distance measures exist to quantify similarities (see, Newman, 2010; Delpini et al., 2013; Barucca et al., 2021; Brunetti et al., 2023). In this paper, we use the notion

[7] Given the richness of our data, we could also adopt $q > 0$ to select the strongest links among nodes.

of cosine similarity (or distance) to measure interconnectedness between any pair of assets i and $j \in \{1, \ldots, S\}$:

$$P^A_{i,j} = \frac{\sum_{k=1}^{N} \overset{\circ}{E}_{i,k} \overset{\circ}{E}_{j,k}}{\left\|\overset{\circ}{E}_{i\cdot}\right\| \left\|\overset{\circ}{E}_{j\cdot}\right\|}, \tag{5}$$

where $\left\|\overset{\circ}{E}_i\right\|$ is the norm of the vector of investors holding asset i (see, Getmansky et al., 2016; Barucca et al., 2021) and $P^A_{i,j}$, the cosine similarity, captures the distance between two non-zero vectors of an inner-product space.[8]

Finally, for each asset i, we aggregate its pair-wise interconnectedness with all other assets j in S where $j \neq i$ and $i, j \in \{1, \ldots, S\}$ to produce an asset-level measure of interconnectedness in this network:

$$IC^A_i = \frac{1}{N(S-1)} \sum_{j \in \{1,\ldots,S\}: j \neq i} P^A_{i,j}. \tag{6}$$

We normalize asset-level interconnectedness by $(S - 1) * N$, where S is the total number of assets and N is the total number of investors, to account for the fact that the number of financial assets and institutions change over time in our data.

[8]There can be alternative definitions of similarity. One option is to use simple counts of the number of portfolios two assets are part of and hence use the following definition for P^A: $P^A = \overset{\circ}{E}(\overset{\circ}{E})^\top$. Another option is to compute these measures using the par amounts held by investors k as a fraction of the amount outstanding of assets k, thereby capturing an intensive margin measure of investor similarity. In this case, we divide each element $E_{i,k}$ from (3) by $\textit{Issue amount outstanding}_i$, and use this new adjacency matrix directly to compute similarity measures P^A. We tested the aforementioned two alternative measures and found that the results were similar to those using cosine similarity on the extensive margin of investors' holdings. Yet another measure of similarity (distance) can be derived from the notion of Euclidean distance, namely, $P^{A'}_{i,j} = \frac{1}{2} \sum_{k=1}^{N} \left|\overset{\circ}{E}_{i,k} - \overset{\circ}{E}_{j,k}\right|$. However, we did not use this measure in our analysis due to the sparsity of the network in our sample.

2.3. An Example: How Shocks Propagate Through an Assets Network

An example may help to explain these concepts. Consider the network below consisting of only three assets and three investors, where the entries in the left matrix represent the dollar amount of each asset held by each investor. This network can be represented by the adjacency matrix $\mathring{\mathbf{E}}_{example}$ on the right:

$$\mathbf{E}_{example} = \begin{array}{c|ccc} & I_1 & I_2 & I_3 \\ \hline A_1 & 6 & 5 & 4 \\ A_2 & 0 & 3 & 2 \\ A_3 & 0 & 0 & 1 \end{array} \qquad \mathring{\mathbf{E}}_{example} = \begin{array}{c|ccc} & I_1 & I_2 & I_3 \\ \hline A_1 & 1 & 1 & 1 \\ A_2 & 0 & 1 & 1 \\ A_3 & 0 & 0 & 1 \end{array}.$$

The top-left cell of the matrix $\mathring{\mathbf{E}}_{example}$ is equal to 1 because investor I_1 has asset A_1 in her portfolio, while 0 in $cell(2,1)$ indicates that investor I_1 has not invested in asset A_2. Using equation (5), we can then compute the cosine similarity metric for any two pairs of assets:

$$\mathbf{P}^{A}_{example} = \begin{array}{c|ccc} & A_1 & A_2 & A_3 \\ \hline A_1 & - & 0.82 & 0.58 \\ A_2 & 0.82 & - & 0.71 \\ A_3 & 0.58 & 0.71 & - \end{array}$$

Accordingly, following equation (6), the vector of interconnectedness measures corresponding to $\mathbf{P}^{A}_{example}$ is:

$$IC^{A}_{example} = \begin{bmatrix} 0.23 \; 0.25 \; 0.21 \end{bmatrix}'$$

The magnitudes of asset-level interconnectedness shown in $IC^{A}_{example}$ indicate that A_2, has the highest level of interconnectedness in the network, followed by A_1 and A_3, which has the lowest interconnectedness. We highlight that that the interconnectedness measure captures a non-linear aspect of the network beyond the simple number of firms investing in each asset, i.e., the assets' degree in the bipartite graph. For example, although A_1 is held by all investors and A_2 is only held by two investors, A_2 is the most central node in this network. A_2's centrality gives rise to a higher asset-level interconnectedness relative to A_1.

Which asset experiences the initial shock plays a fundamental role in determining how a shock propagates through this network. That is, different assets embed different magnitudes of shock propagation. If a shock hits A_2, reducing its market value and the performance of portfolios held by both I_2 and I_3, re-balancing responses by investors I_2 and I_3 create a channel through which the initial shock on A_2 could propagate to A_1 because A_1 and A_2 are commonly held by investors I_2 and I_3. By contrast, an initial shock on A_3 could propagate to other assets through the re-balancing behavior of I_3. Notice that our measure of interconnectedness, as shown in $IC^A_{example}$, conveniently aggregates and quantifies the magnitudes of shock propagation for each asset; the impacts are largest for A_2 (0.25), followed by A_1 (0.23) and A_3 (0.21) in our example.

3. Data

Our analysis relies on data from different sources. Primarily, we use the Thomson Reuters eMAXX database and the Financial Industry Regulatory Authority (FINRA)'s fixed income market Trade Reporting and Compliance Engine (TRACE) database. We supplement these sources with additional data from S&P Global and the Mergent Fixed Income Securities Database (FISD).

3.1. eMAXX

We obtain information on U.S. institutional investors and their 8-digit CUSIP-level bond holdings from the Thomson Reuters eMAXX database, which draws from the quarterly N-CSR, N-CSRS, N-Q, and N-PORT filings with the Security and Exchange Commission (SEC). The data runs from 1998:Q3 until 2021:Q3, and in each quarter we observe the full fixed-income portfolios of all subaccounts belonging to an institutional investor and detailed information of the underlying securities including their ratings, maturities, and coupon rates.

We use several approaches to contain the dimensionality of the network computation. First, we aggregate across all sub-accounts of each institutional investor and also collapse the 8-digit CUSIP-level bond holdings information to the 6-digit issuer-level. In this way, our dataset is simplified and effectively captures how much each institutional investor invests in each issuer (e.g. Ford or IBM).[9] Aside from holdings data which is summed, most 8-digit bond characteristics, such as coupon rates, are weighted-averaged to the 6-digit level. Second, we restrict the sample of institutional investors to the largest investors with assets under management (AUM) within the top 50th percentile of the AUM distribution each quarter, based only on corporate bond AUM.

3.2. TRACE

We obtain security-level data on corporate bond trading volume, liquidity, and volatility from the intraday trading information available from the TRACE database. We aggregate the intraday TRACE data at the quarterly frequency to match the quarterly-level eMAXX dataset. Because trade frequencies are extremely sparse for some bonds, we check the robustness of our analyses by using alternate methods of quarterly aggregation, including the mean, median, and last quarterly observation of each variable.

For bond illiquidity, we use two proxies that are widely adopted in the literature: the Amihud measure and the interquartile range (IQR). Amihud (2002) price impact is defined as:

$$Amihud_{i,t} = \frac{1}{D_{i,t}} \sum_{l=1}^{D_{i,t}} \frac{r_{i,l,t}}{Q_{i,l,t}} \tag{7}$$

[9] See Appendix A for details on identifying unique institutional investors. Using the first six digits of CUSIP to identify issuers follows a well-used practice in the corporate bond literature.

where $D_{i,t}$ is the total number of trades on bond i at time (day) t, and $r_{i,l,t}$ and $Q_{i,l,t}$ refer to the return and traded volume of the lth transaction of bond i on day t, respectively. IQR of traded prices is defined and calculated as the difference between the 75th and the 25th percentiles of daily prices. Volatility of bond prices is measured as the quarterly standard deviation of traded prices of a bond and effectively measures realized volatility at quarterly frequency. As with variables from eMAXX, we collapse the 8-digit CUSIP-level information to the 6-digit issuer-level using outstanding issue amounts as weights.

3.3. Other Data Sources

Additional information for each bond issuance comes from the Mergent Fixed Income Securities Database (FISD). Data include issuer-specific, issue-specific, and transaction information. In addition to basic bond characteristics such as maturity, issuer identity, etc., the database includes pricing at issue (but no pricing information thereafter), ratings, sinking fund and call information including an estimate of the amount outstanding at any given time, covenants, defaults, and more. We obtain the total amount outstanding for each asset and take the mean amount outstanding for each quarter for each CUSIP. We then link this information to the eMAXX holdings data at the CUSIP-quarter level. Since eMAXX does not have complete coverage of bond ratings, we supplement the missing observations with data from FISD that cover ratings from S&P, Fitch, and Moody's.

We supplement missing ratings observations in both eMAXX and FISD with ratings data from the S&P Global database. In the end, roughly 3 million rating observations have been filled in accordingly. The ratings from the three ratings agencies have been transformed into a numerical scale between 1 (lowest) and 21 (highest). We take the average of ratings from S&P, Fitch, and Moody's whenever multiple ratings are available. On the numerical scale, investment-grade bonds are defined as bonds that have ratings equal to or above 12 and high-yield bonds are defined as bonds that have ratings strictly below 12.

4. Network of Corporate Bonds and Interconnectedness

In this section, we describe the structure of the network in the corporate bond market. As mentioned above, we collapse all 8-digit CUSIP-level bond information to the 6-digit issuer-level in all of our empirical analyses (issuers have an average of 38 individual bonds). Throughout the rest of the paper, we interchangeably use *bond* with *issuer* and in this context, *bond*, whenever used, will be referring to the representative bond of the respective issuer.

4.1. Network of Corporate Bonds

Table 1 shows the summary statistics of corporate bond characteristics. Our sample consists of about $200,000$ bonds with an average outstanding amount of about $2 billion, an average remaining maturity of 8 years, and an average coupon rate of 6 percent. Following our numerical conversion of ratings, with the scale of 1 to 21 corresponding to the S&P Global rating of D to AAA, the average rating of 12 in our sample corresponds to a rating of BBB-, which is the lowest rating in investment grade. Because many corporate bonds do not trade often, trade volumes and illiquidity measures show high standard deviations. For instance, an average bond has a median trade volume of about $113 million while minimum and maximum trading volumes each reach as small as $0.11 million and as large as $4.7 billion. Summary statistics on IQR also highlight a sparse network where certain bonds trade more often than others; an average bond has a quarterly median IQR of 0.367 where the smallest and largest IQRs can respectively reach 0.005 and 4.124. Bond price volatility is itself volatile as well.

Figure 2, panel (a), plots the universe of financial institutions investing in corporate bonds as captured in our network. Following the process mentioned in Section 3, our sample contains 112 banks, 543 investment managers, 473 insurance companies, and 114 other funds—or, altogether, 1,242 unique institutional investor identifiers that uniquely appear across the panel in at least one quarter. This sub-sample of the largest institutional investors (quarterly corporate bond AUM above the 50th percentile) represents the lion's share of the total par amount outstanding, about 80% of the total par amount of corporate bonds held within the eMAXX universe. Panel (b) of Figure 2 shows the number of unique corporate bonds in the portfolios of banks, insurance companies, investment managers, and other asset managers as captured in our dataset.

Figure 3 illustrates the network of corporate bonds as defined by our methodology, with each node denoting a corporate bond issuer, and each (weighted) edge connecting two nodes representing the cosine similarity of the overlapping investors holding corporate bonds of the two issuers. Because we compute these networks in each year-quarter, for simplicity, we report the network based on the most recent holdings data, 2021:Q3. Figure 3a represents the full network, with 1,566 bond issuers and 1,020,826 total edges connecting the nodes.[10] Here, the minimum and maximum cosine similarity across all pairs of nodes is 0.017 and 1.0, respectively with an average value of 0.331. The network exhibits a dense core, roughly in two tiers, and a relatively sparser periphery.

Figure 3b portrays a sub-network of the largest 20 corporate bond issuers based on the issued amount outstanding in 2021:Q3. Here, the size of the nodes is scaled according to the total amount of corporate debt outstanding for each issuer. In our data, the corporate bond issuer with the largest amount of corporate debt outstanding is Verizon, with $110 billion. In this sub-network, the minimum and maximum cosine similarity between two corporate bond issuers are 0.501 (Pemex, a Mexican oil firm, and Goldman Sachs) and 0.895 (AT&T and Verizon), respectively. The average pair-wise cosine similarity in this sub-network of the largest corporate bond issuers is 0.751, more than twice as high as the average in the full network, implying a high degree of interconnectedness.

4.2. Interconnectedness in the Corporate Bond Market

Panel A of Table 2 reports summary statistics for the corporate bond issuer-level (cross-section) interconnectedness and other network measures. Because our measure of interconnectedness, the cosine similarity, captures a non-linear aspect of interconnectedness, its sum-

[10] There are fewer than $\binom{1,566}{2}$ edges in the network given that some pairs of nodes have no overlapping investors.

mary statistics read distinctly from those of, say, degree. Normalized to be in the unit interval $[0, 1]$ and by the number of investors and corporate bond issuers in each year-quarter, the average interconnectedness across bonds of the same issuers (6-digit CUSIP) in our sample is 0.034 and the standard deviation is about half of that, suggesting somewhat less variance than linear measures. Figure B3 in the appendix, shows the same information as a cross-sectional distribution, highlighting bi-modality and somewhat lighter tails than a normal distribution.

The degree, as defined in equation (4), relays that an average bond is in the portfolio of 44 investors. It features significant variability, with high standard deviation, and heterogeneity, looking at its minimum and maximum. The strength, as defined in equation (2), refers to the total amount of bonds of a specific issuer (6-digit CUSIP) held by the system and its average is about \$370 million in our sample. There are 7,350 corporate bond issuers that we follow through time and on average an issuer is in the sample for 19 quarters, reflecting the sparsity (minimum 2 quarters, maximum 19.25 years, or 77 quarters) of the network.

Looking at sub-samples in Panel B of Table 2, we find the investor similarity network changes over time. Its dynamics suggest that interconnectedness increased after the Great Financial Crisis (GFC).[11] This is an interesting result. In physical networks, e.g. interbank market, we usually observe a jump-up in connections leading to the crisis, followed by a rapid decrease as a consequence of the increased uncertainty. Our results indicate that the crisis generated higher bond interconnectedness with more corporate bonds held in portfolios of institutional investors. A plausible explanation for this finding is that, after the GFC, institutional investors tried to diversify their holdings and mitigate risk, following traditional finance theory. Various reforms could have also geared institutional investors to hold a similar set of assets that are deemed safer, which might have made corporate bonds more interconnected on average. The effect of interconnectedness on market quality and the volatility of corporate bonds is the subject of the next section.

[11] This change is not a mechanical result due to corporate failures triggered in the aftermath of GFC. In the few cases of M&As or corporate restructures in our sample, 6-digit CUSIPs do not change.

5. Interconnectedness and Market Quality

The advantage of our measures of interconnectedness is that they are specific to a given asset. Given the wealth of information contained in the eMAXX database about corporate bond holdings, we can compute interconnectedness measures aggregated at the issuer level, and we can use those measures in a panel data setting to analyze the relation between the interconnectedness of a bond and its spread, liquidity, and volatility. We can also investigate how this relation is affected during periods of stress with a quantile regression approach. Finally, we test the robustness of our findings by further controlling for other statistics that capture different aspects of the network.

5.1. Mean Effects

To understand the relation between interconnectedness and market quality, we start by investigating the contemporaneous correlation among our variables. In particular, we quantify the relation between interconnectedness and the first moments of an asset—such as spread and liquidity—or its second moments—such as volatility—after controlling for the usual characteristics of the asset including rating, coupon rate, and outstanding amount:

$$Spread_{i,t} = \alpha + \beta_1 IC_{i,t} + \boldsymbol{\gamma}'\mathbf{X}_{i,t} + FE_i + FE_t + \epsilon_{i,t} \tag{8}$$

$$Illiquidity_{i,t} = \alpha + \beta_1 IC_{i,t} + \boldsymbol{\gamma}'\mathbf{X}_{i,t} + FE_i + FE_t + \epsilon_{i,t} \tag{9}$$

$$Volatility_{i,t} = \alpha + \beta IC_{i,t} + \boldsymbol{\gamma}'\mathbf{X}_{i,t} + FE_i + FE_t + \epsilon_{i,t} \tag{10}$$

In Equation (8), the dependent variable is the spread of bond i at time t, measured as the difference between the average yield for all trades on the bond on a given day and the comparable Treasury or interpolated maturity-matched swap rate on the same day, aggregated at the quarterly level. In Equation (9), the dependent variable is illiquidity, computed as either the Amihud measure or the interquantile range (IQR) of traded prices. Finally, in Equation (10), realized volatility is the dependent variable, computed as the quarterly standard deviation of the traded prices of a bond.

In all three equations, the main variable of interest is our measure of corporate bond interconnectedness based on investor similarity for each issuer i's bond (aggregated at the issuer level) at time t, $IC_{i,t}$, which we measure according to Equation (6). $\mathbf{X}_{i,t}$ is a matrix of time-varying bond characteristics that includes credit rating, coupon rate, time to maturity, outstanding issuance size, and trading volume. FE_i refers to issuer fixed effects. FE_t controls for time fixed effects (current year-quarter).

Table 3 presents the results. For ease of interpretation, all variables are standardized to units of their own standard deviation. First, column (1) shows the results of estimating Equation (8). Our measure of interconnectedness is negatively associated with the spread, meaning that an increase in interconnectedness is associated with a decrease in corporate bond spreads. If we interpret spreads as a measure of risk appetite, an increase in interconnectedness increases the appetite for these bonds. Both the statistical and economic magnitudes of this effect are substantial. The coefficient is significant at the 1% level and a one-standard deviation increase in interconnectedness lowers the spread by 44.9 basis points, corresponding to about one-sixth of a standard deviation, controlling for everything else. This magnitude is substantially larger than the effect of a one standard deviation change in most control variables including coupon rate, time to maturity, outstanding issuance amount, and trade volume, and is only smaller than that of credit ratings. This is consistent with the well-known fact that a bond's credit rating is the predominant factor in determining corporate bond investment demand.

Columns (2) and (3) show the results of estimating Equation (9) using the two different measures of illiquidity. The coefficients for interconnectedness are significant at the 1% level and carry negative signs, meaning that an increase in interconnectedness is associated with a decrease (increase) in corporate bond illiquidity (liquidity). Specifically, a one-standard deviation increase in interconnectedness is associated with a 0.15 standard deviation decrease in Amihud illiquidity and a 0.11 standard deviation decrease in the IQR measure.

Finally, column (4) shows the results of estimation Equation (10). Interconnectedness has a negative coefficient on corporate bond volatility, implying that higher interconnectedness is associated with lower volatility. A one standard deviation increase in interconnectedness is associated with a 0.07 standard deviation decrease in realized volatility. The effect is, again, statistically significant at the 1% level.

It is also noteworthy that all of our estimated coefficients for interconnectedness remain significant even after controlling for the "size" of the bond, measured by outstanding issuance amount and trade volume. It implies that this nonlinear measure of corporate bond centrality does not simply capture the linear size aspects of the corporate bond network (e.g., number of investors) and that assets which are common to many portfolios are more liquid, less volatile, and have lower spreads.

More specifically, the role of interconnectedness seems to be more important for high-yield bonds, as opposed to investment-grade bonds. Table 4 shows the results of running the same estimation equations as before on sub-samples of investment grade (in Panel A) and high-yield bonds (in Panel B), respectively. In column (1), the magnitude of the slope coefficient on interconnectedness is smaller for investment-grade bonds (-0.158) compared to high-yield bonds (-0.545). Both are statistically significant at the 1-percent level. In contrast, the association of interconnectedness with illiquidity seems to be stronger for investment-grade bonds, as shown in column (2). Interconnectedness, again, has a stronger negative coefficient for volatility for high-yield bonds, as shown in column (4). We examine the full distributional quantile effects of interconnectedness in the next section.

5.2. Quantile Regression Analysis

Measures of conditional central tendency do not always adequately characterize the statistical relations among variables. In fact, we think it is particularly interesting to estimate the conditional quantiles of spread, illiquidity, and volatility as a function of interconnectedness and a vector of covariates. In other words, when we think about financial stability considerations, we are actually interested in the tails of the distributions. In particular, we care about the right tail, corresponding to stressful market situations when spreads and volatility are high and illiquidity is high.

Figure 4 illustrates the results of quantile regressions between interconnectedness and our bond market quality measures: spread, illiquidity, and realized volatility. While the overall negative linkages between interconnectedness and spread, illiquidity, and volatility is still evident, the results from this analysis show the estimated coefficients are much larger in the right tail, when corporate bond markets are under stress. For example, looking at spreads in Figure 4a, a one standard deviation increase in interconnectedness has very small associations with spread below the median. Only above the median does interconnectedness begin to bear a negative association in large magnitudes, leading up to around 150 basis points in spread reduction from one standard deviation increase in interconnectedness. Results based on illiquidity and realized volatility in Figure 4b and Figure 4c are similar. A one standard deviation increase in interconnectedness is associated with larger reductions in IQR as the quantile increases, reaching up to nearly one standard deviation reduction in IQR and about half of a standard deviation in realized volatility, in the highest quantile.

Overall, the quantile results show that when volatility and spreads are high, and liquidity is scarce, an increase in interconnectedness is associated with a larger improvement in market conditions. At the opposite end of the spectrum, when volatility and spreads are low, and liquidity is abundant, the link between interconnectedness and market conditions is less important (estimated parameters are close to zero).

5.3. Robustness

Any measure of interconnectedness could be, to some extent, endogenously correlated with conventional asset characteristics or other measures that capture different aspects of the network. For this reason, we check the robustness of our results in two ways: 1) examining the descriptive statistics of our control variables by interconnectedness decile and 2) controlling for additional network statistics that capture other characteristics of the network.

We use five control variables in our regressions: credit rating, coupon rate, time to maturity, outstanding issuance size, and trading volume. Table 5 shows the summary statistics of these variables grouped by deciles of bond interconnectedness. Importantly, credit rating, which is the most predominant determinant of bond investment, does not vary significantly across bonds with different levels of interconnectedness. Such a result suggests that our measure of interconnectedness, cosine similarity, is not picking up a correlated variation purely arising from differences in credit rating characteristics of the bonds in our sample.

Time to maturity also does not exhibit a clear correlation pattern with interconnectedness deciles, although extremely high levels of interconnnectedness seem to be associated with a lower time to maturity, highlighting investors' preferences for shorter maturity bonds. Outstanding issuance amounts and trading volumes in lower interconnectedness deciles are also low, which is simply by construction: corporate bonds with large issuance amounts and large trading volumes naturally imply that these bonds are likely to be in the portfolio of many investors. The only variable that seems to be meaningfully associated across different deciles of interconnectedness is coupon rate. Higher coupon rates are observed in lower deciles of interconnectedness and the rates decline with interconnectedness deciles. This implies some comovement between coupon rates and interconnetedness such that bonds with higher rates are not commonly held by many financial investors. If higher coupon rates are associated with a higher perceived risk by market participants, our results indicate that investors prefer to invest in less risky assets.

Table 6 estimates Equations (8)-(10), additionally controlling for two new variables, investor concentration, as measured by the Herfindahl-Hirschman Index (HHI), and degree, as defined in equation (4). There has been an emerging literature in asset pricing on how institutional investors can affect prices and qualities of various financial assets including corporate bonds (Bretscher et al., 2022; Coppola, 2021; Haddad and Muir, 2021, among others). For instance, Li and Yu (2022) find a negative association between investor concentration and transaction turnover and liquidity, and a positive association between investor concentration and spread. We measure investor concentration with the HHI and show results in Panel A of Table 6. While the HHI is significant across specifications, coefficients for interconnectedness in all four columns remain statistically significant at the 1% level and also economically significant, though the magnitudes are slightly smaller than in Table 3.

On the other hand, controlling for degree, which counts the number of unique financial institutions that hold each corporate bond, can allow us to examine whether our measure of interconnectedness is simply picking up the number of investors holding that corporate bond. Panel B in Table 6 shows the results of the regressions controlling for degree. All of the interconnectedness coefficients in the regressions for spread, illiquidity, and volatility remain negative and significant at the 1% level, with very small variation in the size of the coefficients compared to Table 3. Finally, Panel C controls for both HHI and degree and shows similar results to those from Panels A and B.

The robustness analyses above offer us preliminary evidence of unique variations that our measure of interconnectedness carries above and beyond what conventional bond characteristics and alternative statistics of networks can offer. Given the effectiveness of this measure, we now turn to investigating the mechanism linking interconnectedness with market characteristics.

6. Interconnectedness and Risk Sharing

Does interconnectedness allow risk sharing and hence help mitigate the effects of a negative shock to the financial system? Or does interconnectedness exacerbate the effects of a shock through contagion? This is a fundamental question in the network literature. The model in Allen and Gale (2000) suggests that a complete network (where every node is linked to another) is beneficial in mitigating the effects of a shock while Acemoglu et al. (2015) show that the overall effect depends on the size of the shock.

While our empirical analyses in Section 5 provides evidence of a net positive link between interconnectedness and market quality, there may be times when risk sharing can play an even more significant role in improving market functioning. In this section, we propose two identification strategies to study the causal effect of interconnectedness on the corporate bond market. We look at the COVID-19 outbreak and fallen angels. Through these two specific events, we isolate shocks that affect only a subset of bonds in our sample and analyze the impact of interconnectedness across groups that were differentially affected by the shocks.

6.1. Evidence from COVID-19 Outbreak

The outbreak of COVID-19 in March 2020 introduced a purely exogenous bifurcation of firms by adversely affecting those belonging to a certain set of industries, such as transportation and retail, and not affecting those belonging to other industries, such as household goods and utility. Let us call the bonds issued by firms in COVID-affected industries "COVID-exposed bonds" and those issued by firms in industries not affected "COVID-unexposed bonds." This bifurcation provides us with an ideal laboratory to examine whether the impact of the initial shock on COVID-exposed bonds was mitigated by their interconnectedness to unexposed bonds, that is whether interconnectedness allows risk sharing and therefore helps absorb the effect of a shock as implied by Allen and Gale (2000).

We obtain data on each issuer's exposure to COVID-19 using textual analysis of quarterly earnings call transcripts (Hassan et al., 2023). The exposure to COVID-19 is measured by counting the number of times the word "COVID" appears around a negative or positive sentiment word, normalized by the total number of words in the transcript (Loughran and McDonald, 2011). We first rank each firm by its net sentiment score in 2020. Firms with a high score are the firms most exposed to the COVID-19 shock. Hence, we define COVID-exposed bonds as bonds issued by firms with sentiment score belonging to the top 25 percent of the distribution and COVID-unexposed bonds as bonds issued by firms with sentiment scores in the middle 25 percent (between the 37.5 and 62.5 percentiles).[12]

[12] We use the middle 25 percent as our control group instead of the bottom of the net sentiment distribution to avoid capturing any other portfolio re-balancing effects due to bonds that actually benefited from the COVID-19 outbreak, such as healthcare.

Then, for the group of COVID-exposed bonds, we estimate the following equations for t =2020:Q1 and $t-1$ =2019:Q4:

$$Spread_{i,t}^{exposed} = \alpha + \beta_1 IC_{i,t-1}^{unexposed} + \boldsymbol{\gamma}'\mathbf{X}_{i,t} + FE_i + FE_t + \epsilon_{i,t} \tag{11}$$

$$Illiquidity_{i,t}^{exposed} = \alpha + \beta_1 IC_{i,t-1}^{unexposed} + \boldsymbol{\gamma}'\mathbf{X}_{i,t} + FE_i + FE_t + \epsilon_{i<t} \tag{12}$$

$$Volatility_{i,t}^{exposed} = \alpha + \beta IC_{i,t-1}^{unexposed} + \boldsymbol{\gamma}'\mathbf{X}_{i,t} + FE_i + FE_t + \epsilon_{i,t}, \tag{13}$$

where $Spread_{i,t}^{exposed}$, $Illiquidity_{i,t}^{exposed}$, and $Volatility_{i,t}^{exposed}$ refer to spreads, illiquidity and volatility of exposed bonds at time t, while $IC_{i,t-1}^{unexposed}$ indicates the cosine similarity interconnectedness measure between exposed and unexposed bonds at time $t-1$. These regressions explore the relation between the interconnectedness of COVID-exposed bonds to the bonds that would be eventually unexposed immediately before the COVID outbreak and the performance of these bonds in the quarter that COVID became salient. Importantly, computing interconnectedness at time $t-1$, before the shock which, by definition, is unpredictable, allows us to address all possible endogeneity issues.

Table 7 Panel A shows the results. Interconnectedness of COVID-exposed bonds to unexposed bonds matters for spread and the Amihud measure of illiquidity. A one standard deviation increase in interconnectedness of exposed bonds to unexposed bonds is associated with a 75.4 basis points decline in spread and a 0.4 standard deviation decline in Amihud illiquidity. Both effects are statistically significant at the 1% level. These magnitudes are substantially higher—2/3 larger for spread and more than two times as large for Amihud illiquidity—than those from the mean effects for the whole panel in Table 3. The coefficients of interconnectedness in the IQR and realized volatility regressions are not statistically significant. Overall, the results show that, for COVID-exposed bonds, being interconnected to unexposed bonds enabled risk sharing and hence was beneficial.

We can also investigate the opposite case to see how the unexposed bonds fared due to their interconnectedness to exposed bonds. To do so we run the same regressions as above but on the sample of unexposed bonds:

$$Spread_{i,t}^{unexposed} = \alpha + \beta_1 IC_{i,t-1}^{exposed} + \gamma X_{i,t} + FE_i + FE_t + \epsilon_{i,t} \tag{14}$$

$$Illiquidity_{i,t}^{unexposed} = \alpha + \beta_1 IC_{i,t-1}^{exposed} + \gamma X_{i,t} + FE_i + FE_t + \epsilon_{i,t} \tag{15}$$

$$Volatility_{i,t}^{unexposed} = \alpha + \beta IC_{i,t-1}^{exposed} + \gamma X_{i,t} + FE_i + FE_t + \epsilon_{i,t} \tag{16}$$

Table 7 Panel B shows the results. Contrary to the previous findings from COVID-exposed bonds, interconnectedness is not statistically significant for spread and both measures of illiquidity. However, interconnectedness of unexposed bonds to COVID-exposed bonds matters for the realized volatility of exposed bonds, as can be seen in column (4). Specifically, as the interconnectedness of unexposed bonds to COVID-exposed bonds increased by one standard deviation, the realized volatility of unexposed bonds *increased* by about a quarter of standard deviation. This effect is statistically significant at the 1% level. Overall, the results are also consistent with the risk sharing argument: bonds of firms not affected by COVID take up some of the risk of COVID-exposed bonds. Interconnectedness allows risk sharing without material consequences on spreads and liquidity of COVID-unexposed bonds.

6.2. Evidence from Fallen Angels

Credit ratings play an integral part in corporate bond investment, and rating downgrades are major events that affect the demand and market characteristics of the bond, such as liquidity. Downgrades are especially more significant events when the corporate bond is downgraded from the lowest credit rating in investment grade (BBB-) to high yield. These bonds are called "fallen angels." The change from investment grade to high yield involves an entire identity change in the bond's membership, and many institutional investors such as insurers have investment mandates on how much exposure they can carry with regard to high-yield investment. Spreads widen, liquidity drops, and volatility increases for most fallen angels.

We are interested in studying interconnectedness and market characteristics when some bonds become fallen angels. From our data, we sample corporate bonds with an average credit rating between BBB- (the lowest investment grade) and BBB. Within this sub-sample, we consider which bond is downgraded in the next period. Again, the bifurcation of whether a bond becomes a fallen angel or not is plausibly exogenous within this narrow window. The idea is that, by considering only two time periods, $t-1$, before the downgrade, and t, when the downgrade occurs, insulate our analysis from endogeneity concerns.

We measure interconnectedness of 580 fallen angels in our sample with respect to the bonds that did not get downgraded and estimate the same three Equations (11)-(13) to test if interconnectedness continues to play an important role in the bond's market spreads, liquidity, and volatility. Table 8 shows the results. Interconnectedness continues to reduce spreads and improve liquidity for this sub-sample of fallen angels. Our results show that a one standard deviation increase in interconnectedness of a fallen angel is associated with a 62 basis points decrease in its spread and about one third of a standard deviation of illiquidity measures; the effects are statistically significant at the 1% level. The economic magnitudes are, as with the case with COVID-related results from the Section 6.1, substantially higher than those from the mean effects for the whole panel in Table 3, implying a particularly large role of interconnectedness in market quality of fallen angels.[13]

The findings even around these major corporate events suggest that interconnectedness has an explanatory power over market characteristics of corporate bonds above and beyond what can be conventionally measured through a standard set of market-based data such as credit rating, coupon rate, and time to maturity.

[13] Results for the sub-sample of corporate bonds that were not downgraded are reported in Table B1.

7. Conclusion

In this paper, we develop an alternative and complementary network structure derived at the asset level and based on the idea that assets are interconnected if they are held by the same investors. We focus on the corporate bond market to investigate the link between interconnectedness and spread, liquidity, and volatility of corporate bonds. We find that the higher the interconnectedness—meaning that the asset is common to many investors' portfolios—the lower its spread and the higher its liquidity. This result highlights that, as expected, corporate bonds that are held across several portfolios are those that require a lower compensation for risk and that are more liquid. This relation is, however, affected by market conditions. We explore the heterogeneous links of interconnectedness throughout the conditional distribution of the response variables (spreads, liquidity, and volatility), while controlling for individual and time-specific bond characteristics, through a panel data quantile regression. We find that the relation we have just highlighted is stronger when a financial asset is under stress, i.e., when the spread and illiquidity of an asset are in the upper tails of their conditional distributions. Importantly, interconnectedness mitigates the effects of negative shocks in the financial system through risk sharing. The COVID-19 and "fallen angels" analyses allow us to claim a causal effect in the sense that higher interconnectedness improves market functioning.

Our results shed light on the role of interconnectedness in financial markets. They provide an important contribution to the debate on whether a more connected network is beneficial to markets. Our contributions are relevant to academia as well as to policy makers. In times of distress, any policy intervention facilitating the creation of edges—i.e. allowing the network to be more dense—would improve market conditions. In fact, any policy intervention in crisis periods tends to restore confidence and, hence, facilitate market functioning, making markets and institutions more interconnected.

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Tables and Figures

Table 1
Basic Statistics on Bond Characteristics in the Network

This table presents summary statistics of bond-level characteristics in our network, aggregated at each issuer level. Spread is calculated as yield minus the Treasury rate of comparable maturity. Rating is calculated as the average rating of three rating agencies, S&P, Fitch, and Moody's, where the categorical ratings are transformed into a numerical scale between 1 (lowest rating) and 21 (highest rating). Volatility is calculated as the standard deviation of daily traded price during each quarter. We use two measures of bond illiquidity, the Amihud (2002) price impact measure (per $mil) and the interquartile range ("IQR") of daily traded prices. All variables are winsorized at the top and bottom 1 percentiles. Source: eMAXX, FISD, S&P Global, and TRACE.

Variable	Obs	Mean	Std. Dev.	Min	Max
Outstanding issue amount ($bil)	192,399	1.961	3.669	0.035	23.72
Remaining maturity (quarter)	191,016	33.24	24.08	3	119
Coupon rate	189,699	6.188	2.101	1.516	11.601
Spread (quarterly mean)	192,399	3.150	3.278	-0.857	19.28
Spread (quarterly median)	192,399	3.116	3.251	-0.882	19.06
Spread (last quarterly observation)	192,399	3.107	3.367	-1.200	19.86
Rating	185,036	12.02	3.987	4	21
Trade volume (quarterly mean; $mil)	192,399	307.85	462.29	0.20	11,980
Trade volume (quarterly median; $mil)	192,399	112.69	183.47	0.11	4,715
Trade volume (last quarterly observation; $mil)	192,399	248.91	1049.00	0.00	239,900
Price Volatility	192,399	1.641	1.460	0.022	11.14
Illiquidity: Amihud (quarterly mean)	192,399	0.003	0.009	0	0.230
Illiquidity: Amihud (quarterly median)	192,399	0.001	0.002	0	0.035
Illiquidity: Amihud (last quarterly observation)	144,758	0.002	0.005	0	0.032
Illiquidity: IQR (quarterly mean)	192,399	0.526	0.497	0.006	5.032
Illiquidity: IQR (quarterly median)	192,399	0.367	0.410	0.005	4.124
Illiquidity: IQR (last quarterly observation)	142,341	0.626	0.756	0.012	4.348

Table 2
Corporate Bond Interconnectedness and Other Network Measures

This table presents summary statistics for the interconnectedness and other network measures of corporate bonds used in this paper. Panel A reports the summary statistics for the cross-section of corporate bonds (aggregated at the issuer level). Specifically, for each bond, we take the arithmetic average of the variables across the time period in which that bond appears in the sample. The Number of Quarters variable captures how many quarters a particular bond is in the sample. Panel B reports the summary statistics broken down into several time periods during our sample period. Strength is defined as in equation (2) and refers to the total amount of the corporate bond of a specific issuer held by the system. Degree is defined as in equation (4) and refers to the total number of investors investing in a specific corporate bond. Cosine similarity is defined as in Equation (6) and is in basis points. Source: eMAXX and authors' calculations.

Panel A: Cross-section of Corporate Bonds								
Variables	*N*	*Mean*	*Median*	*Std. Dev.*	*Minimum*	*Maximum*	*Skew.*	*Kurt.*
Cosine Similarity	7,350	0.034	0.033	0.015	0.0019	0.067	-01.30	208.2
Degree	7,350	44.37	32.78	40.46	1	294	2.04	8.71
Strength ($mil)	7,350	369,524	178,285	625,914	512	6,458,448	4.51	29.35
Number of Quarters	7,350	18.98	11	18.89	2	77	1.43	4.22

Panel B: Bond-Quarter Panel								
Variables	*N*	*Mean*	*Median*	*Std. Dev.*	*Minimum*	*Maximum*	*Skew.*	*Kurt.*
	2002:Q3–2021:Q3							
Cosine Similarity	192,242	0.0406	0.0413	0.0159	0	0.0794	-21.3	220.3
Degree	192,242	69.91	49	63.69	1	510	1.848	7.330
Strength ($mil)	192,242	1.983e+06	377,254	7.005e+06	1	2.401e+08	12.26	234.1
	2002:Q3–2008:Q4							
Cosine Similarity	51,907	0.0278	0.0281	0.0104	0	0.0794	-18.6	253.6
Degree	51,907	53.32	35	55.01	1	510	2.562	12.11
Strength ($mil)	51,907	476,083	196,299	868,356	1	3.510e+07	6.251	90.93
	2009:Q1–2021:Q3							
Cosine Similarity	140,335	0.0454	0.0479	0.0149	0.00000601	0.0776	-61.8	275.6
Degree	140,335	76.05	56	65.56	1	496	1.683	6.506
Strength ($mil)	140,335	2.540e+06	516,578	8.111e+06	2	2.401e+08	10.61	175.4

Table 3
Analysis of Corporate Bond Interconnectedness versus Spread, Liquidity, and Volatility

This table presents results from the analysis of interconnectedness and spread, illiquidity, and realized volatility using Equations (8), (9), and (10), aggregated at the issuer level. In column (1), the dependent variable is spread of a corporate bond issuer i's average bond at time t, measured as the yield for all trades for each of issuer i's bond over comparable Treasury or interpolated maturity-matched swap rate on the same day, and aggregated at the quarterly-level (median). In columns (2) and (3), the dependent variables are illiquidity of bond i at time t, measured following Amihud (2002) and interquartile range (IQR) of trade prices (quarterly medians), respectively. In column (4), the dependent variable is volatility of bond i at time (quarter) t, measured as the standard deviation of trade prices of bond i during each quarter. In all columns, the main variable of interest is "interconnectedness," which we measure by cosine similarity based on Equation (5). Credit rating has been converted from the average of the three rating agencies, S&P, Fitch, and Moody's to a numerical scale between 1 (lowest) and 21 (highest). Time to maturity is in quarters. Outstanding issuance amount and trade volume (quarterly median) are in log($thous). For ease of reading, most variables have been transformed into units of standard deviation. Source: eMAXX, FISD, S&P Global, TRACE, and authors' calculation.

	(1) Spread	(2) Std(Amihud illiquidity)	(3) Std(IQR of traded prices)	(4) Std(Realized volatility)
Std(Interconnectedness)	-0.449***	-0.152***	-0.114***	-0.066***
	(0.062)	(0.018)	(0.015)	(0.016)
Std(Rating)	-2.431***	-0.205***	-0.317***	-0.373***
	(0.143)	(0.021)	(0.022)	(0.031)
Std(Coupon rate)	0.376***	-0.132***	-0.107***	-0.078***
	(0.054)	(0.016)	(0.013)	(0.015)
Std(Time to maturity)	-0.021**	0.016***	0.019**	0.018***
	(0.010)	(0.005)	(0.008)	(0.005)
Std(Outstanding issue amount)	0.295***	0.325***	0.222***	0.020
	(0.056)	(0.023)	(0.019)	(0.013)
Std(Trade volume)	-0.264***	-0.464***	-0.281***	
	(0.025)	(0.019)	(0.016)	
FE	Issuer, time	Issuer, time	Issuer, time	Issuer, time
Observations	182,607	182,607	182,607	182,607
R-squared	0.702	0.468	0.439	0.464

Table 4
Interconnectedness of Investment Grade and High Yield Bonds

This table presents results from the analysis of interconnectedness and spread, illiqudity, and realized volatility using Equations (8), (9), and (10), aggregated at the issuer level, for the sub-sample of investment grade and high yield bonds in Panels A and B, respectively. In column (1), the dependent variable is spread of corporate bond issuer i's average bond at time t, measured as the yield for all trades for each of issuer i's bond over comparable Treasury or interpolated maturity-matched swap rate on the same day, and aggregated at the quarterly-level (median). In columns (2) and (3), the dependent variables are the illiquidity of bond i at time t, measured following Amihud (2002) and the interquartile range (IQR) of traded prices (quarterly medians), respectively. In column (4), the dependent variable is the volatility of bond i at time (quarter) t, measured as the standard deviation of traded prices of bond i during each quarter. In all columns, the main variable of interest is "interconnectedness," which we measure by cosine similarity based on Equation (5). Credit rating has been converted from the average of the three rating agencies, S&P, Fitch, and Moody's to a numerical scale between 1 (lowest) and 21 (highest). Time to maturity is in quarters. Outstanding issuance amount and trade volume (quarterly median) are in log($thous). For ease of reading, most variables have been transformed into units of standard deviation. Source: eMAXX, FISD, S&P Global, TRACE, and authors' calculation.

	(1) Spread	(2) Std(Amihud illiquidity)	(3) Std(IQR of traded prices)	(4) Std(Realized volatility)
	Panel A: Investment-grade bonds			
Std(Interconnectedness)	-0.158***	-0.209***	-0.126***	-0.00762
	(0.0270)	(0.0251)	(0.0194)	(0.0149)
Std(Rating)	-0.839***	-0.113***	-0.149***	-0.124***
	(0.0695)	(0.0352)	(0.0288)	(0.0292)
Std(Coupon rate)	0.176***	-0.111***	-0.0418***	0.0578***
	(0.0248)	(0.0253)	(0.0152)	(0.0130)
Std(Time to maturity)	0.114***	0.165***	0.223***	0.259***
	(0.0172)	(0.0132)	(0.0119)	(0.0119)
Std(Outstanding issue amount)	0.0567**	0.340***	0.198***	-0.0462***
	(0.0227)	(0.0234)	(0.0190)	(0.0103)
Std(Trade volume)	-0.119***	-0.432***	-0.263***	
	(0.0112)	(0.0202)	(0.0161)	
FE	Issuer, time	Issuer, time	Issuer, time	Issuer, time
Observations	109,332	109,332	109,332	109,332
R-squared	0.669	0.480	0.468	0.547
	Panel B: High-yield bonds			
Std(Interconnectedness)	-0.545***	-0.136***	-0.126***	-0.113***
	(0.0759)	(0.0208)	(0.0200)	(0.0222)
Std(Rating)	-3.400***	-0.336***	-0.489***	-0.642***
	(0.157)	(0.0342)	(0.0338)	(0.0465)
Std(Coupon rate)	0.546***	-0.126***	-0.141***	-0.148***
	(0.0724)	(0.0175)	(0.0181)	(0.0209)
Std(Time to maturity)	-0.335***	0.0955***	0.155***	0.192***
	(0.0959)	(0.0261)	(0.0230)	(0.0206)
Std(Outstanding issue amount)	0.676***	0.412***	0.348***	0.136***
	(0.0739)	(0.0326)	(0.0287)	(0.0203)
Std(Trade volume)	-0.451***	-0.556***	-0.356***	
	(0.0370)	(0.0240)	(0.0236)	
FE	Issuer, time	Issuer, time	Issuer, time	Issuer, time
Observations	73,243	73,243	73,243	73,243
R-squared	0.713	0.520	0.470	0.481

Table 5
Corporate Bond Characteristics by Interconnectedness Decile

This table presents summary statistics for corporate bond characteristics for each decile of interconnectedness, as measured by the cosine similarity. These characteristics are averaged across the full sample time period, from 2002:Q3 to 2021:Q3. Credit rating has been converted from the average of the three rating agencies, S&P, Fitch, and Moody's to a numerical scale between 1 (lowest) and 21 (highest). Time to maturity is in quarters. Outstanding issuance amount and trade volume (quarterly median) are in $billion. Source: eMAXX, FISD, S&P Global, TRACE, and authors' calculation.

Decile	Rating	Coupon rate	Time to maturity	Outstanding issue amount ($bil)	Trade volume ($bil)
1	10.92	7.24	109.54	0.27	81.53
2	10.41	7.45	149.16	0.31	95.76
3	10.74	7.22	82.83	0.45	105.99
4	10.97	6.81	188.91	0.51	109.07
5	10.75	6.75	124.82	0.65	106.14
6	11.13	6.36	91.24	0.80	104.63
7	11.39	6.02	173.37	1.16	105.69
8	11.93	5.70	106.88	2.21	109.49
9	11.96	5.41	41.75	3.26	136.11
10	11.41	4.93	41.85	3.97	162.64

Table 6
Robustness Using Other Network Measures

This table presents results from running the same analysis of interconnectedness and spread, liquidity, and volatility using Equations (8), (9), and (10) and now controlling for two additional variables, investor concentration as measured by Herfindahl-Hirschman Index (HHI) in Panel A and degree in Panel B. Panel C controls for both HHI and degree. In column (1), the dependent variable is spread of a corporate bond issuer i's average bond at time t, measured as the yield for all trades for each of issuer i's bond over comparable Treasury or interpolated maturity-matched swap rate on the same day, and aggregated at the quarterly-level (median). In columns (2) and (3), the dependent variables are illiquidity of bond i at time t, measured following Amihud (2002) and interquartile range (IQR) of trade prices (quarterly medians), respectively. In column (4), the dependent variable is volatility of bond i at time (quarter) t, measured as the standard deviation of trade prices of bond i during each quarter. In all columns, the main variable of interest is "interconnectedness," which we measure by cosine similarity based on Equation (5). Credit rating has been converted from the average of the three rating agencies, S&P, Fitch, and Moody's to a numerical scale between 1 (lowest) and 21 (highest). Time to maturity is in quarters. Outstanding issuance amount and trade volume (quarterly median) are in log($thous). For ease of reading, most variables have been transformed into units of standard deviation. Results for rating, coupon rate, time to maturity, outstanding issue amount, and trade volume are shown in Appendix B. Source: eMAXX, FISD, S&P Global, TRACE, and authors' calculation.

	Panel A: HHI			
	(1) Spread	(2) Std(Amihud illiquidity)	(3) Std(IQR of traded prices)	(4) Std(Realized volatility)
Std(Interconnectedness)	-0.336***	-0.126***	-0.092***	-0.052***
	(0.060)	(0.018)	(0.016)	(0.017)
Std(HHI)	0.150***	0.034***	0.029***	0.018**
	(0.028)	(0.011)	(0.009)	(0.007)
FE	Issuer, time	Issuer, time	Issuer, time	Issuer, time
Observations	182,607	182,607	182,607	182,607
R-squared	0.702	0.468	0.439	0.464
	Panel B: Degree			
	(1) Spread	(2) Std(Amihud illiquidity)	(3) Std(IQR of traded prices)	(4) Std(Realized volatility)
Std(Interconnectedness)	-0.449***	-0.186***	-0.130***	-0.0541***
	(0.062)	(0.019)	(0.016)	(0.016)
Std(Degree)	0.002	0.129***	0.062***	-0.044***
	(0.042)	(0.018)	(0.016)	(0.014)
FE	Issuer, time	Issuer, time	Issuer, time	Issuer, time
Observations	182,607	182,607	182,607	182,607
R-squared	0.702	0.470	0.440	0.464

Table 6
Robustness Using Other Network Measures Cont'd

	Panel C: HHI and Degree			
	(1) Spread	(2) Std(Amihud illiquidity)	(3) Std(IQR of traded prices)	(4) Std(Realized volatility)
Std(Interconnectedness)	-0.326***	-0.165***	-0.110***	-0.037**
	(0.062)	(0.019)	(0.017)	(0.017)
Std(HHI)	0.152***	0.026**	0.025***	0.022***
	(0.028)	(0.010)	(0.009)	(0.008)
Std(Degree)	-0.030	0.123***	0.056***	-0.049***
	(0.043)	(0.018)	(0.016)	(0.014)
FE	Issuer, time	Issuer, time	Issuer, time	Issuer, time
Observations	182,607	182,607	182,607	182,607
R-squared	0.702	0.470	0.440	0.464

Table 7
Interconnectedness of COVID-exposed and -unexposed Bonds

This table presents results from the analysis on effects of interconnectedness for the sub-sample of bonds that were severely stressed ("exposed") and not stressed ("unexposed") by COVID-19 outbreak respectively in Panels A and B, using Equations (11)–(16). The dependent variables are spread of a corporate bond issuer i's average bond at time t, measured as the yield for all trades for each of issuer i's bond over comparable Treasury or interpolated maturity-matched swap rate on the same day, and aggregated at the quarterly-level (median); illiquidity of bond i at time t, measured based on Amihud (2002) and using interquartile range (IQR) of trade prices (quarterly medians); and volatility of bond i at time (quarter) t, measured as the standard deviation of trade prices of bond i during each quarter. The main variable of interest is cosine similarity of COVID-exposed bonds with unexposed bonds, based on Equation (5). Credit rating has been converted from the average of the three rating agencies, S&P, Fitch, and Moody's to a numerical scale between 1 (lowest) and 21 (highest). Time to maturity is in quarters. Outstanding issuance amount is in log($thous). For ease of reading, most variables have been transformed into units of standard deviation. Source: eMAXX, FISD, S&P Global, TRACE, and authors' calculation.

t = 2020Q1, t-1 = 2019Q4	(1) Spread	(2) Std(Amihud illiquidity)	(3) Std(IQR of traded prices)	(4) Std(Realized volatility)
	Panel A: COVID-exposed bonds			
Std(IC to unexposed bonds$_{t-1}$)	-0.754***	-0.394***	-0.293	0.006
	(0.213)	(0.080)	(0.073)	(0.091)
Std(Rating$_t$)	-1.743***	-0.350***	-0.340***	-0.305***
	(0.154)	(0.058)	(0.053)	(0.063)
Std(Coupon rate$_t$)	0.285*	-0.158***	-0.022	0.159**
	(0.159)	(0.060)	(0.054)	(0.067)
Std(Time to maturity$_t$)	0.285**	0.150***	0.192***	0.338***
	(0.132)	(0.050)	(0.045)	(0.055)
Std(Outstanding issue amount$_t$)	0.508**	0.643***	0.428***	0.053
	(0.249)	(0.094)	(0.086)	(0.088)
Std(Trade volume$_t$)	-0.053	-0.784***	-0.300***	
	(0.186)	(0.070)	(0.064)	
FE	Issuer, time	Issuer, time	Issuer, time	Issuer, time
Observations	278	278	278	278
R-squared	0.451	0.385	0.204	0.207
	Panel B: COVID-unexposed bonds			
Std(IC to exposed bonds$_{t-1}$)	-0.140	-0.119	-0.052	0.243***
	(0.105)	(0.083)	(0.069)	(0.087)
Std(Rating$_t$)	-0.890***	-0.289***	-0.192***	-0.240***
	(0.078)	(0.062)	(0.052)	(0.064)
Std(Coupon rate$_t$)	0.608***	-0.022	0.024	0.266***
	(0.0822)	(0.065)	(0.055)	(0.069)
Std(Time to maturity$_t$)	0.084	0.038	0.019	0.138***
	(0.056)	(0.045)	(0.037)	(0.047)
Std(Outstanding issue amount$_t$)	0.137	0.535***	0.105	0.020
	(0.102)	(0.081)	(0.068)	(0.075)
Std(Trade volume$_t$)	0.001	-0.713***	-0.187***	
	(0.078)	(0.062)	(0.052)	
FE	Issuer, time	Issuer, time	Issuer, time	Issuer, time
Observations	322	322	322	322
R-squared	0.594	0.336	0.115	0.196

Table 8
Interconnectedness of Fallen Angels

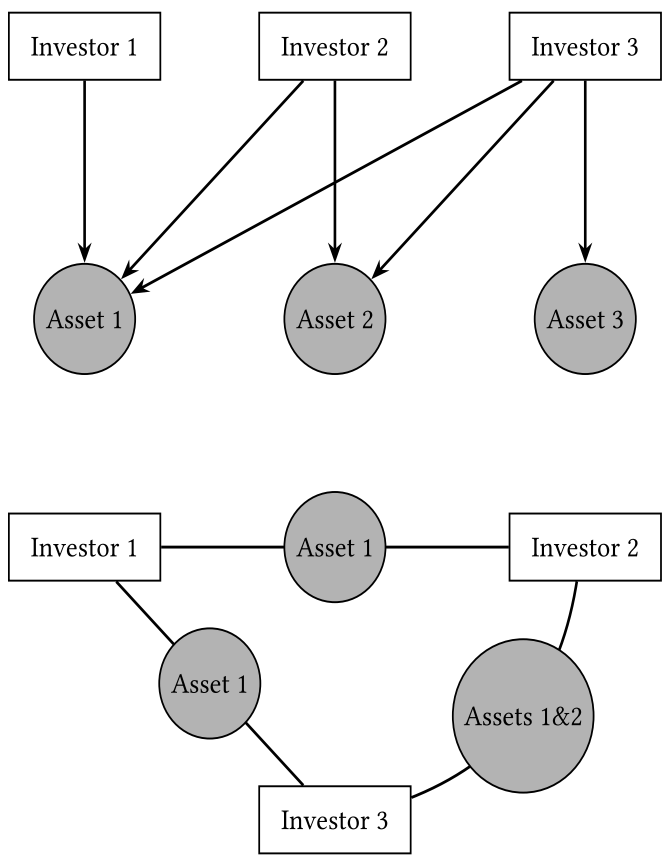
This table presents results from the analysis on effects of interconnectedness for the sub-sample of bonds whose average credit rating from the three rating agencies was between BBB- (the lowest investment grade) and BBB in the previous period and became fallen angels, using Equations (11)-(13). The dependent variables are spread of a corporate bond issuer i's average bond at time t, measured as the yield for all trades for each of issuer i's bond over comparable Treasury or interpolated maturity-matched swap rate on the same day, and aggregated at the quarterly-level (median); illiquidity of bond i at time t, measured based on Amihud (2002) and using interquartile range (IQR) of trade prices (quarterly medians); and volatility of bond i at time (quarter) t, measured as the standard deviation of trade prices of bond i during each quarter. In all columns, the main variable of interest is "interconnectedness," which we measure by cosine similarity based on Equation (5). Credit rating has been converted from the average of the three rating agencies, S&P, Fitch, and Moody's to a numerical scale between 1 (lowest) and 21 (highest). Time to maturity is in quarters. Outstanding issuance amount is in log($thous). For ease of reading, most variables have been transformed into units of standard deviation. Source: eMAXX, FISD, S&P Global, TRACE, and authors' calculation.

	(1) Spread	(2) Std(Amihud illiquidity)	(3) Std(IQR of traded prices)	(4) Std(Realized volatility)
Std(Interconnectedness)	-0.619***	-0.343***	-0.289***	-0.148
	(0.214)	(0.084)	(0.099)	(0.097)
Std(Rating)	-2.313***	-0.469***	-0.290*	-0.314*
	(0.363)	(0.142)	(0.167)	(0.165)
Std(Coupon rate)	0.518***	-0.103	0.082	-0.040
	(0.192)	(0.075)	(0.088)	(0.087)
Std(Time to maturity)	-0.086	-0.028	-0.028	0.0006
	(0.083)	(0.033)	(0.038)	(0.038)
Std(Outstanding issue amount)	0.390**	0.714***	0.590***	0.225***
	(0.177)	(0.069)	(0.081)	(0.076)
Std(Trade volume)	0.052	-0.770***	-0.558***	
	(0.121)	(0.048)	(0.056)	
FE	Time	Time	Time	Time
Observations	580	580	580	580
R-squared	0.643	0.515	0.447	0.454

Figure 1
Illustration of Networks Based on Overlapping Portfolios vs. Investors

Sub-figure (a) illustrates the conventional network of financial institutions, or investors, constructed via their overlapping portfolios. In this example, Investor 1 holds positive amounts of Assets 1, Investor 2 holds positive amounts of Assets 1 and 2, and Investor 3 holds positive amounts of all three assets. The resulting network of overlapping portfolios has connections between all investors through their common holdings of Asset 1 or Assets 1 and 2. Sub-figure (b) depicts our new network of financial assets constructed via the overlapping investors. Notice that the focus is now on assets and the arrows are flipped, enabling the interpretation that Asset 1 is held by all investors, Asset 2 is held by Investors 2 and 3, and Asset 3 is held only by Investor 3. In this network of overlapping investors, Assets 1 and 2 are connected via their common exposure to Investors 2 and 3, Assets 1 and 3 are connected through Investor 3, and Assets 2 and 3 are connected through Investor 3.

(a) Network of Overlapping Portfolios



(b) Network of Overlapping Investors

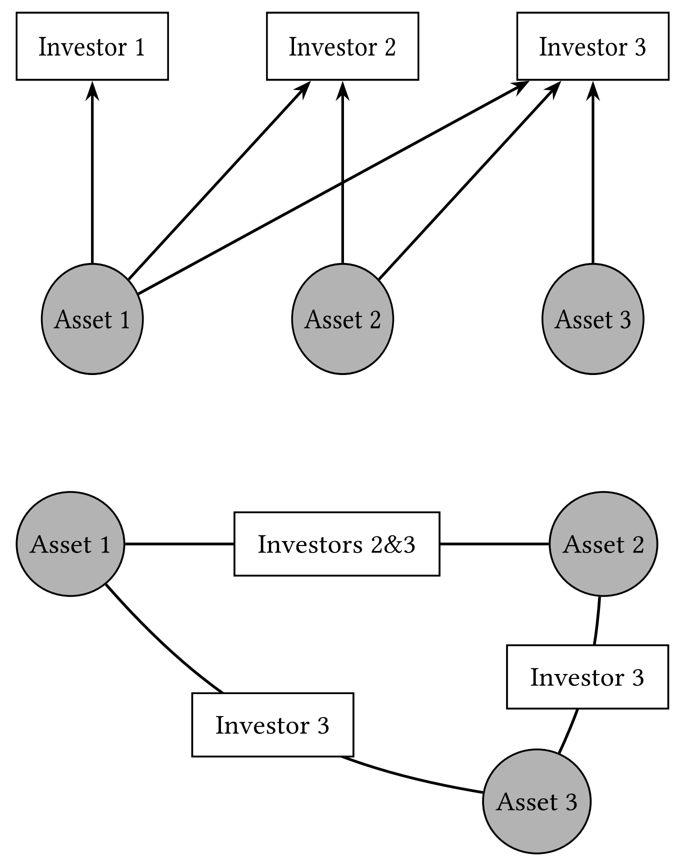
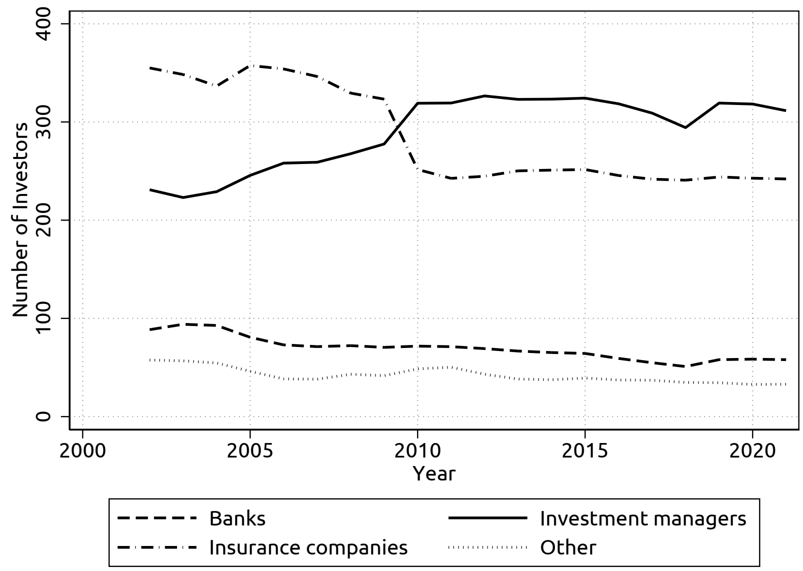


Figure 2
Number of Financial Institutions and Corporate Bonds in the Network

Sub-figure (a) plots the number of unique investors in the network of financial investors (institutions) and corporate bonds. Investor types were carefully verified and assigned via a manual auditing process; see Appendix A for more details. Sub-figure (b) plots the number of unique corporate bonds held by these investors over time. Quarterly figures are averaged within a year. Sources: eMAXX and authors' calculation.

(a) Number of Unique Investors



(b) Number of Unique Corporate Bonds

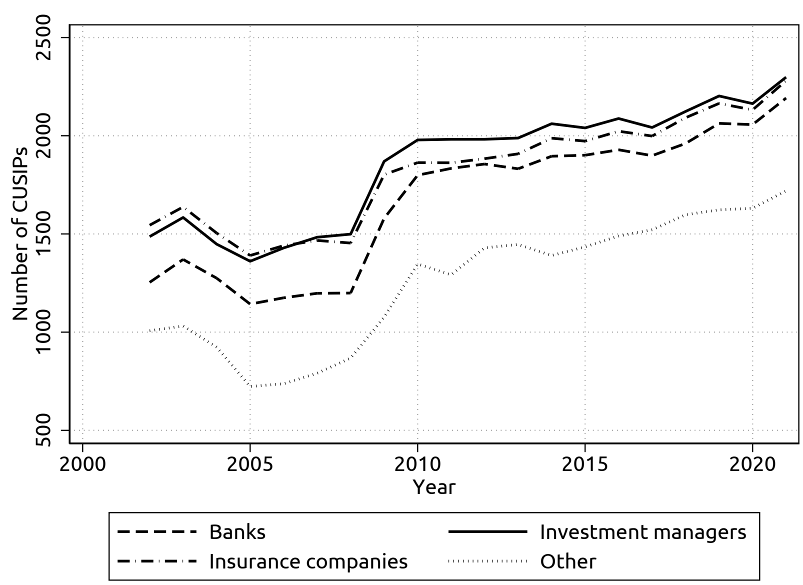
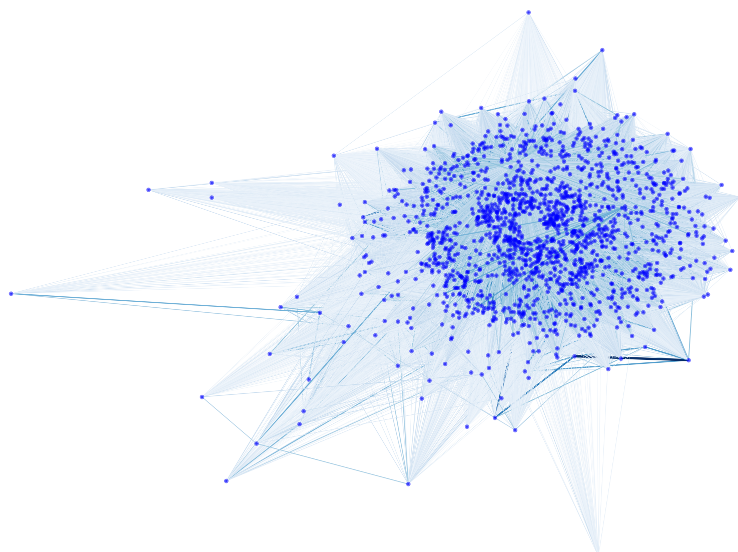


Figure 3
Network of Corporate Bonds Based on Overlapping Investors

This figure shows the network of corporate bonds based on overlapping investors. Each node is a corporate bond issuer, and the (weighted) edges between two nodes capture the cosine similarity of the overlapping investors holding the corporate bonds of the two issuers. Sub-figure (a) shows the entire network in 2021:Q3; sub-figure (b) shows the sub-network of the largest 20 corporate bond issuers in 2021:Q3. Sources: eMAXX and authors' calculation.

(a) Full network



(b) Network of bond issuers with largest amount outstanding

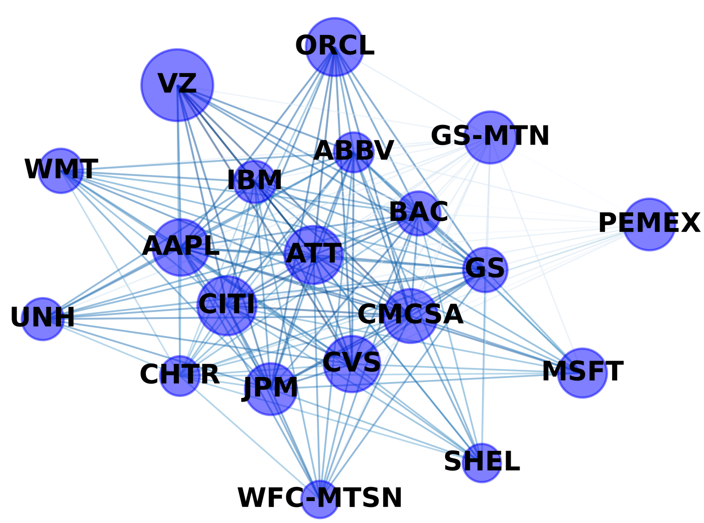
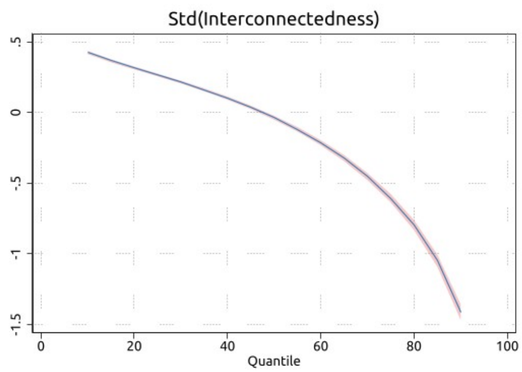


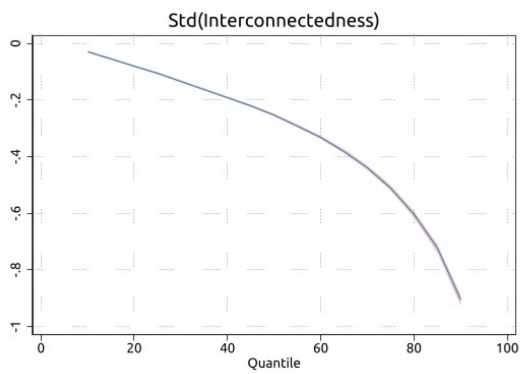
Figure 4
Quantile Regressions

This figure illustrates the results of quantile regressions between interconnectedness measures and bond market quality measures (spread, illiquidity, and realized volatility.) Source: eMAXX, TRACE, and authors' calculations.

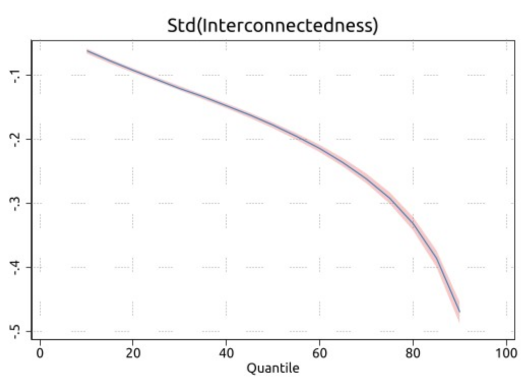
(a) Spread



(b) Illiquidity (IQR)



(c) Realized Volatility



Appendix A Additional Details on Data

A.1 Cleaning eMAXX

- We drop observations for which the external manager is not disclosed (`firmid = 0`). Because we focus on institutional investors, we also drop observations relating to the holdings of co-managed subaccounts.
- There are some instances in which the market sector of a CUSIP changes over time. To enforce consistency of this variable over time, we collapse the market sector variable to its modal value for each CUSIP.
- We supplement the eMAXX holdings data with further detail on the institutional investors, including the reported investor name, type, and headquarters location. All U.S. institutional investors, with the exception of pension funds, are mandated to report their entire portfolio each quarter, a rule that has been in effect since May 2004.[14] Thus, we focus on the set of investors domiciled in the United States (`firm_domicile = "USA"`).
- We initially sort institutional investors into four types based on the `firm_code` variable.
  1. Banks: BKM, BKT, BMS, BFM, BKP
  2. Investment managers: INM
  3. Insurance companies: ILF, IMD, IND, IPC, REI
  4. Pension/other firms: GPE, UPE, CPE; EQM, FEN, GVT, HGE, CRP, CRU, FCC, HLC, OTG, SVG, TRT, UIT
- Because the eMAXX data distinguish between the subsidiaries of institutional investors, for example, JP Morgan Chase (New York) and JP Morgan Chase (Los Angeles), some investors belonging to a single parent company (i.e., JP Morgan Chase) are coded with different investor identifiers. This property of the data is inconvenient given our research objective of constructing networks that link assets together based on overlap-

[14] https://www.sec.gov/rules/final/33-8393.htm.

ping investors. We do not wish to differentiate between an institutional investor's subsidiaries' bond portfolios, so we aggregate these subsidiaries' bond holdings into a single institutional investor portfolio.

To identify and aggregate information at the parent level, we utilize a string matching algorithm on the reported institutional investor names to match investors that plausibly belong to the same parent company, but which potentially receive separate investor identifiers in eMAXX. Following the string matching algorithm, we then conduct a manual audit on the matches to ensure their validity. Ultimately, we obtain a dictionary mapping parent companies to their subsidiaries and use this dictionary to replace the subsidiaries' identifiers with a new investor identifier. Finally, we aggregate the bond holdings data to the institutional investor level. Following the string matching algorithm, we identify 4,972 unique institutional investors. While eMAXX reports a type for each institutional investor (see Appendix A.2), we uncovered several discrepancies between the true type of an investor and the type reported by eMAXX (for example, JP Morgan Chase is classified as a mutual fund). We therefore further audit the investor type in the final set of institutional investors and categorize each investor as a bank, investment manager, insurance company, or other investor type.

- We focus on the top market players in terms of assets under management. Specifically, for each quarter, we rank the asset managers in terms of their assets under management observed in the eMAXX universe, which we construct directly from the holdings data. Next, we take the distribution of firms' AUM based on this ranking, and select the firms whose AUM falls within the top 50th percentile (right tail) of the distribution of firms' AUM in that quarter. Finally, we select the median number of firms across the entire sample period to include in the network analysis.

- The eMAXX data also has information on the market sector to which each security belongs: asset-backed securities, including collateralized debt obligations and covered bonds; corporate bonds, including high-yield and investment grade; government bonds, including sovereign and government agency; mortgage-backed securities, including agency and private label pass through, collateralized mortgage obligations, collateralized mortgage-backed securities, and residential mortgage-backed securities;

regional and municipal bonds, including U.S. muni and international cities, states, and provinces; private placements, including 144A and non-144A; and emerging markets. For the scope of this paper, we only use those securities that belong to the corporate bond market sector.

A.2 Institutional Investor and Subaccount Types in eMAXX

This table reports the institutional investor and subaccount types included in the eMAXX data. There are four types of institutional investor types—banks, investment managers, insurance companies, and other investors—and four types of subaccount types—insurance investment accounts, mutual funds, pension funds, and other funds.

Institutional Investor Type	**Subaccount Type**
Banks	*Insurance Investment Accounts*
Bank-Management Division	Insurance Co-Diversified
Bank-Portfolio	Insurance Co-Life/Health
Bank-Savings/Bldg Society	Insurance Co-Prop & Cas
Bank-Trust	*Mutual Funds*
Broker/Dealer-Fund Mgr	Mut Fd-O/E/Unit Tr/SICAV
Broker/Management Sub	Mut Fd-C/E/Invst Tr
Investment Managers	Mutual Fund-Equity
Investment Manager	Mutual Fund-Fund of Funds
Mutual Fund Manager	*Pension Funds*
Insurance Companies	Pension Fund-Corporate
Insurance Co-Diversified	Pension Fund-Government
Insurance Co-Life	Pension Fund-Union
Insurance Co-Mgmt Div	*Other Funds*
Insurance Co-Prop & Cas	401K
Reinsurance Company	Annuity/Variable Annuity
Other Investors	Bank-Portfolio
Pension Fund-Government	Bank-Trust
Pension Fund-Union	Church/Religious Org
Corporation	Corporation
Credit Union	Credit Union
Equity Manager	Finance Company
Finance/Credit Company	Fonds Commun de Placement
Foundation/Endowment	Foundation/Endowment
Government	Health Care Systems
Health Care Systems	Hedge Fund
Hedge Fund	Hospital
Nuclear De-Comm Trust	Investment Manager
Other-General	Nuclear De-Comm Trust
Pension Fund-Corporate	Other
Trust Company	Small Business Invst Co
Unit Investment Trust	Unit Investment Trust

Appendix B   Additional Tables and Figures

Table B1
Interconnectedness of Bonds That Did Not Become Fallen Angels

This table presents results from the analysis on effects of interconnectedness for the sub-sample of bonds sub-sample of corporate bonds whose average credit rating from the three rating agencies was between BBB- and BBB in the previous period but luckily did not become fallen angels, using Equations (8)-(10). The dependent variables are spread of a corporate bond issuer i's average bond at time t, measured as the yield for all trades for each of issuer i's bond over comparable Treasury or interpolated maturity-matched swap rate on the same day, and aggregated at the quarterly-level (median); illiquidity of bond i at time t, measured based on Amihud (2002) and using interquartile range (IQR) of trade prices (quarterly medians); and volatility of bond i at time (quarter) t, measured as the standard deviation of trade prices of bond i during each quarter. In all columns, the main variable of interest is "interconnectedness," which we measure by cosine similarity based on Equation (5). Credit rating has been converted from the average of the three rating agencies, S&P, Fitch and Moody's to a numerical scale between 1 (lowest) and 21 (highest). Time to maturity is in quarters. Outstanding issuance amount is in log($thous). For ease of reading, most variables have been transformed into units of standard deviation. Source: eMAXX, FISD, S&P Global, TRACE, and authors' calculation.

	(1) Spread	(2) Std(Amihud illiquidity)	(3) Std(IQR of traded prices)	(4) Std(Realized Volatility)
Std(Interconnectedness)	-0.379***	-0.306***	-0.275***	-0.064***
	(0.0183)	(0.013)	(0.013)	(0.011)
Std(Rating)	-1.471***	-0.202***	-0.422***	-0.263***
	(0.089)	(0.062)	(0.065)	(0.054)
Std(Coupon rate)	0.454***	-0.033***	0.040***	0.208***
	(0.0147)	(0.0102)	(0.011)	(0.009)
Std(Time to maturity)	0.017***	0.011***	0.019***	0.0006
	(0.005)	(0.004)	(0.004)	(0.003)
Std(Outstanding issue amount)	0.138***	0.432***	0.319***	0.067***
	(0.017)	(0.012)	(0.012)	(0.009)
Std(Trade volume)	-0.019*	-0.452***	-0.304***	
	(0.011)	(0.007)	(0.008)	
FE	Time	Time	Time	Time
Observations	16,570	16,570	16,570	16,570
R-squared	0.494	0.298	0.290	0.386

Table B2
Robustness Using Other Network Measures: Full Results

This table presents the full results from running the same analysis of interconnectedness and spread, liquidity, and volatility using Equations (8), (9), and (10) and now controlling for two additional variables, investor concentration as measured by Herfindahl-Hirschman Index (HHI) in Panel A and degree in Panel B. Panel C controls for both HHI and degree. In column (1), the dependent variable is spread of a corporate bond issuer i's average bond at time t, measured as the yield for all trades for each of issuer i's bond over comparable Treasury or interpolated maturity-matched swap rate on the same day, and aggregated at the quarterly-level (median). In columns (2) and (3), the dependent variables are illiquidity of bond i at time t, measured following Amihud (2002) and interquartile range (IQR) of trade prices (quarterly medians), respectively. In column (4), the dependent variable is volatility of bond i at time (quarter) t, measured as the standard deviation of trade prices of bond i during each quarter. In all columns, the main variable of interest is "interconnectedness," which we measure by cosine similarity based on Equation (5). Credit rating has been converted from the average of the three rating agencies, S&P, Fitch and Moody's to a numerical scale between 1 (lowest) and 21 (highest). Time to maturity is in quarters. Outstanding issuance amount and trade volume (quarterly median) are in log($thous). For ease of reading, most variables have been transformed into units of standard deviation. Source: eMAXX, FISD, S&P Global, TRACE, and authors' calculation.

	Panel A: HHI			
	(1) Spread	(2) Std(Amihud illiquidity)	(3) Std(IQR of traded prices)	(4) Std(Realized volatility)
Std(Interconnectedness)	-0.336***	-0.126***	-0.092***	-0.052***
	(0.060)	(0.018)	(0.016)	(0.017)
Std(Rating)	-2.407***	-0.199***	-0.312***	-0.370***
	(0.142)	(0.022)	(0.022)	(0.031)
Std(Coupon rate)	0.389***	-0.129***	-0.104***	-0.077***
	(0.054)	(0.016)	(0.013)	(0.015)
Std(Time to maturity)	-0.021**	0.016***	0.019**	0.018***
	(0.010)	(0.005)	(0.008)	(0.005)
Std(Outstanding issue amount)	0.317***	0.330***	0.226***	0.023*
	(0.056)	(0.023)	(0.019)	(0.013)
Std(Trade volume)	-0.268***	-0.465***	-0.281***	
	(0.025)	(0.019)	(0.016)	
Std(HHI)	0.150***	0.034***	0.029***	0.018**
	(0.028)	(0.011)	(0.009)	(0.007)
FE	Issuer, time	Issuer, time	Issuer, time	Issuer, time
Observations	182,607	182,607	182,607	182,607
R-squared	0.702	0.468	0.439	0.464

Table 5
Robustness Using Other Network Measures (cont'd)

Panel B: Degree				
	(1) Spread	(2) Std(Amihud illiquidity)	(3) Std(IQR of traded prices)	(4) Std(Realized volatility)
Std(Interconnectedness)	-0.449***	-0.186***	-0.130***	-0.0541***
	(0.062)	(0.019)	(0.016)	(0.016)
Std(Rating)	-2.431***	-0.221***	-0.325***	-0.367***
	(0.143)	(0.021)	(0.022)	(0.030)
Std(Coupon rate)	0.376***	-0.127***	-0.104***	-0.080***
	(0.054)	(0.016)	(0.013)	(0.015)
Std(Time to maturity)	-0.021**	0.019***	0.020**	0.017***
	(0.010)	(0.005)	(0.008)	(0.006)
Std(Outstanding issue amount)	0.293***	0.256***	0.189***	0.044***
	(0.060)	(0.024)	(0.020)	(0.014)
Std(Trade volume)	-0.264***	-0.465***	-0.281***	
	(0.025)	(0.019)	(0.016)	
Std(Degree)	0.002	0.129***	0.062***	-0.044***
	(0.042)	(0.018)	(0.016)	(0.014)
FE	Issuer, time	Issuer, time	Issuer, time	Issuer, time
Observations	182,607	182,607	182,607	182,607
R-squared	0.702	0.470	0.440	0.464

Panel C: HHI and Degree				
	(1) Spread	(2) Std(Amihud illiquidity)	(3) Std(IQR of traded prices)	(4) Std(Realized volatility)
Std(Interconnectedness)	-0.326***	-0.165***	-0.110***	-0.037**
	(0.062)	(0.019)	(0.017)	(0.017)
Std(Rating)	-2.403***	-0.216***	-0.320***	-0.363***
	(0.142)	(0.022)	(0.022)	(0.031)
Std(Coupon rate)	0.388***	-0.125***	-0.102***	-0.075***
	(0.054)	(0.016)	(0.013)	(0.015)
Std(Time to maturity)	-0.021**	0.019***	0.020**	0.017***
	(0.010)	(0.005)	(0.008)	(0.006)
Std(Outstanding issue amount)	0.333***	0.263***	0.195***	0.049***
	(0.062)	(0.024)	(0.021)	(0.014)
Std(Trade volume)	-0.267***	-0.466***	-0.282***	
	(0.025)	(0.019)	(0.016)	
Std(HHI)	0.152***	0.026**	0.025***	0.022***
	(0.028)	(0.010)	(0.009)	(0.008)
Std(Degree)	-0.030	0.123***	0.056***	-0.049***
	(0.043)	(0.018)	(0.016)	(0.014)
FE	Issuer, time	Issuer, time	Issuer, time	Issuer, time
Observations	182,607	182,607	182,607	182,607
R-squared	0.702	0.470	0.440	0.464

Figure B1
Shares of Corporate Bond Holdings by Investor Type

This figure depicts how much each investor type holds out of the total outstanding amount of bonds in our final sample of bond holding data. Each point represents the sum of bond holdings by the investor type—as shown in eMAXX—divided by the sum of outstanding amount of the bonds based on FISD. Bonds in eMAXX and FISD are matched based on CUSIPs. Quarterly statistics are averaged within each year. Sources: eMAXX and FISD.

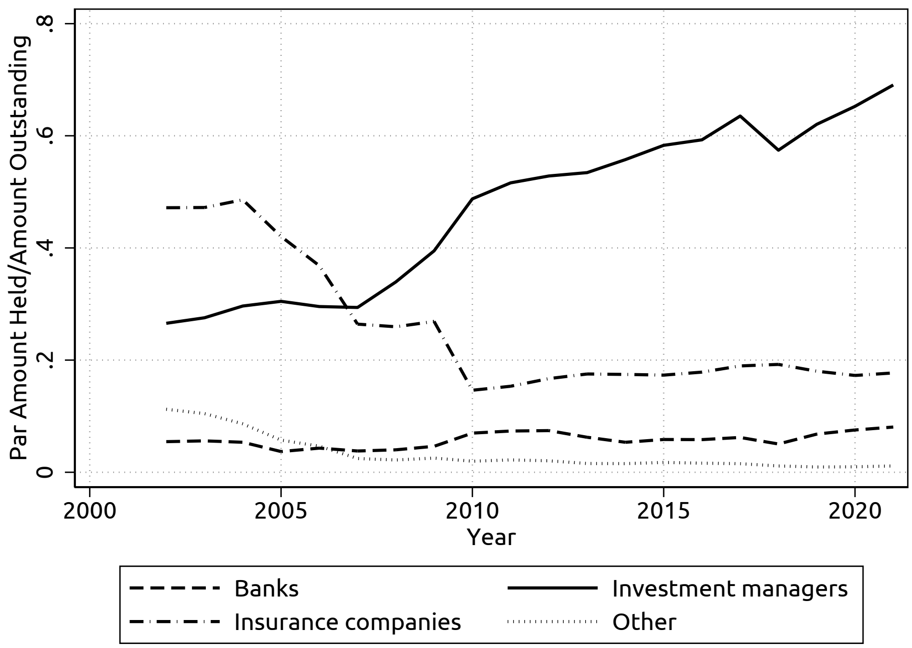


Figure B2
Number of Quarters a Bond Appears in Our Sample

This figure shows the distribution of the number of quarters a bond appears in our data (bond is aggregated at the issuer level). Sources: eMAXX.

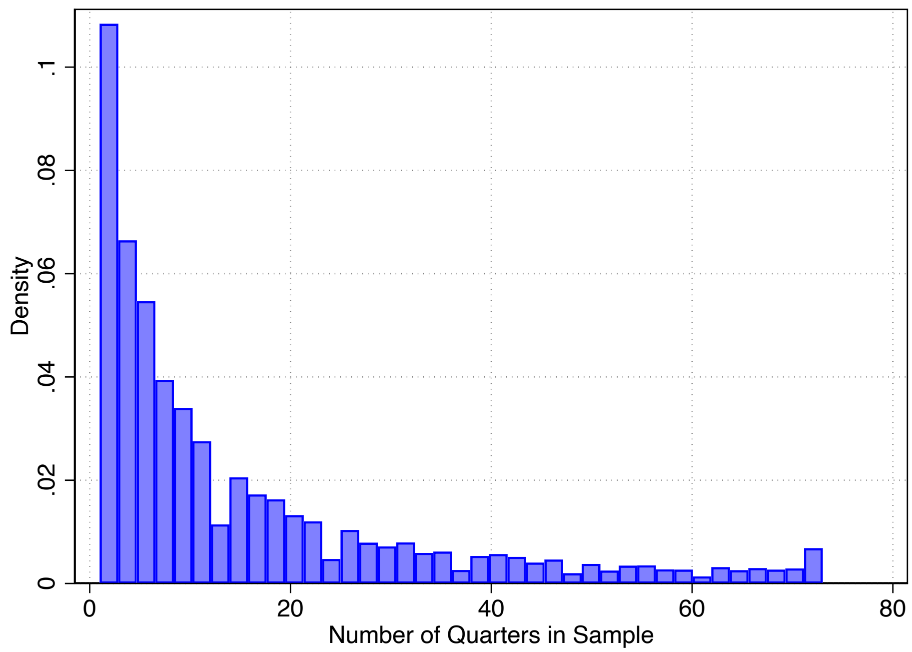


Figure B3
Cross-sectional Distribution of Interconnectedness of Corporate Bonds

This figure shows the distribution of interconnectedness, as measured by cosine similarity, in the cross-section of corporate bonds in our sample (aggregated at the issuer level). Specifically, for each bond, we take the arithmetic average of our interconnectedness measure across the time period in which that bond appears in the sample. Source: eMAXX and authors' calculation.

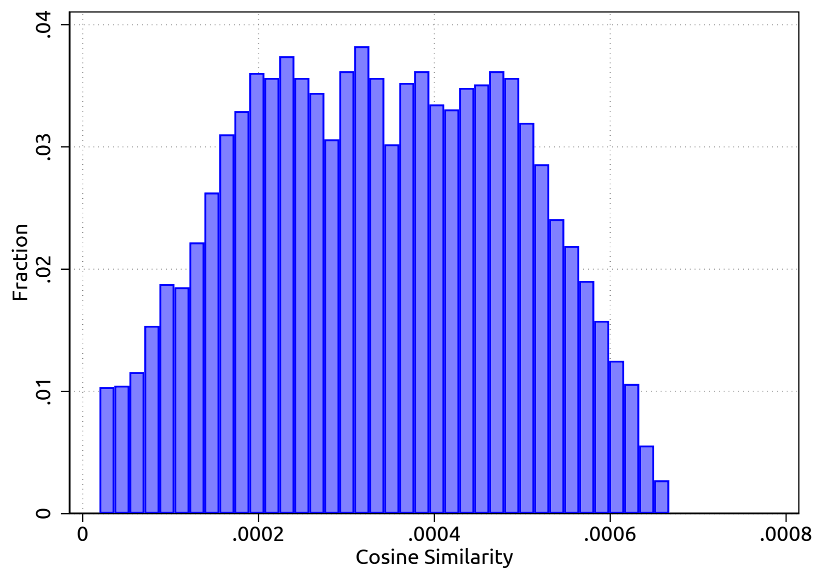
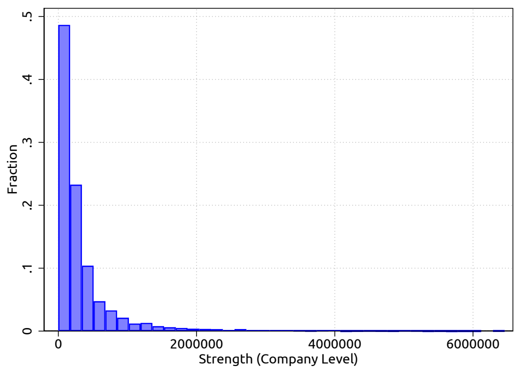


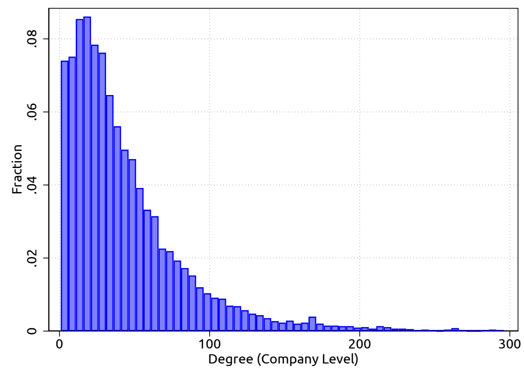
Figure B4
Cross-Sectional Distributions of Other Network Measures

This figure shows the distribution of other network measures in the cross-section of corporate bonds in our sample (aggregated at the issuer level). Specifically, for each bond, we take the arithmetic average of the variables across the time period in which that bond appears in the sample. Sources: eMAXX and authors' calculation.

(a) Strength



(b) Degree



(c) Number of Overlapping Investors